

M21 RT Semantic Sensitivity

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Setup

Load libraries

1. Set ggplot2 parameters

Load Files and Format Files

Load Files

```
#DIR <- "csv_files"
df_a <- read_csv("rt_data_hc_A.csv")
df_b <- read_csv( "rt_data_hc_B_fixed.csv")
frq_w <- read_csv("frq_cw.csv")
frq_nw <- read_csv("frq_nw.csv")
dmg <- read_csv("demo_lang_vsl_pca_hc.csv")
```

Format Files

```
# Concatenate datasets
rt <- bind_rows(AB = df_a,
                 BA = df_b,
                 .id = "List")
rt_dmg<- right_join(dmg, rt, join_by(SubjID == subject_nr)) |> # Join Participant Demographic and Lang Data
               mutate(target = tolower(target)) |>
               filter(correct == 1)

# Divide into Experimental and Filler Items
rt_fill <- rt_dmg |> filter(str_detect(targ_type, "^FILL"))
rt_exp <- rt_dmg |> filter(!str_detect(targ_type, "^FILL"))

# Add logFS to frequency datasets
frq_w <- frq_w |> mutate(Log10FS = log10(FS))
frq_nw <- frq_nw |> mutate(Log10FS = log10(FS))

# Define Factors and Conditions
rt_exp_format <- rt_exp |>
  separate(targ_type, into = c("trial_type", "family_size", "complexity"), sep = "_",
           remove = TRUE, extra = "drop", fill = "right")

# Divide into Words and Nonwords
rt_words <- rt_exp_format |> filter(trial_type == "CW") |> select(-complexity)
rt_nwords <- rt_exp_format |> filter(trial_type == "NW")

# Join Stimulus Frequency Data
rt_words_frq <- left_join(rt_words, frq_w, join_by(target))|>
  select(-cond_trig.y, -word_trig.y) |>
  rename(cond_trig = cond_trig.x, word_trig = word_trig.x) # remove duplicate columns
rt_nwords_frq <- left_join(rt_nwords, frq_nw, join_by(target==word)) |>
  select(-cond_trig.y, -word_trig.y) |>
  rename(cond_trig = cond_trig.x, word_trig = word_trig.x)

# Rename BF_Split and FS_Split columns
rt_words_frq <- rt_words_frq |> rename(Base_Frequency = BF_Split, Family_Size = FS_Split) # Rename BF_Split and FS_Split columns
rt_nwords_frq <- rt_nwords_frq |> rename(Base_Frequency = BF_Split, Family_Size = FS_Split)

# Recode factor levels
# rt_words_frq <- rt_words_frq |>
#   mutate(Base_Frequency = case_match(Base_Frequency, "Low" ~ "Low BF", "High" ~ "High BF"),
```

```

#           Family_Size = case_match(Family_Size, "Small" ~ "Small Family", "Large" ~ "Large Family"))
# rt_nwords_frq <- rt_nwords_frq |> mutate(Base_Frequency = case_match(Base_Frequency, "Low" ~ "Low BF", "High" ~ "High BF"),
# #                                         Family_Size = case_match(Family_Size, "Small" ~ "Small Family", "Large" ~ "Large Family"))
#
# rt_words_frq$Semantic_Sensitivity[rt_words_frq$Semantic_Sensitivity == "Low"] <- "Low Sensitivity"
# rt_words_frq$Semantic_Sensitivity[rt_words_frq$Semantic_Sensitivity == "High"] <- "High Sensitivity"

```

Word Data

Use `complete.cases()` to find which rows have missing data in the model-relevant variables:

```

# Specify only the variables used in the model
model_vars_w <- c("response_time", "Log10BF", "BF", "FS", "Family_Size", "Base_Frequency", "Semantic_Sensitivity", "SubjID")

# Identify incomplete rows cohort 1
incomplete_cases_words <- rt_words_frq[!complete.cases(rt_words_frq[, model_vars_w]), ]
rt_words_cmpl <- rt_words_frq[complete.cases(rt_words_frq[, model_vars_w]), ]
# View them
print(incomplete_cases_words)

# Standardize the predictors
rt_words_cmpl$Log10BF_std <- as.numeric(scale(rt_words_cmpl$Log10BF, center = TRUE, scale = TRUE))
rt_words_cmpl$FS_std <- as.numeric(scale(rt_words_cmpl$FS, center = TRUE, scale = TRUE))
rt_words_cmpl$Log10WF_std <- as.numeric(scale(rt_words_cmpl$Log10WF, center = TRUE, scale = TRUE))
rt_words_cmpl$Log10FS_std <- as.numeric(scale(rt_words_cmpl$Log10FS, center = TRUE, scale = TRUE))
rt_words_cmpl$Dim.2_std <- as.numeric(scale(rt_words_cmpl$Dim.2, center = TRUE, scale = TRUE))

```

Anova

```

anova_model_words <- mixed(
  response_time ~ Base_Frequency * Family_Size * Semantic_Sensitivity +
  (1 | SubjID) +
  (1 | STRING),
  data = rt_words_cmpl,
  method = "S")
anova_model_words

## Mixed Model Anova Table (Type 3 tests, S-method)
##
## Model: response_time ~ Base_Frequency * Family_Size * Semantic_Sensitivity +
## Model:   (1 | SubjID) + (1 | STRING)
## Data: rt_words_cmpl
##          Effect      df     F p.value
## 1           Base_Frequency 1, 92.29 10.15 **   .002
## 2           Family_Size   1, 92.30  9.28 **   .003
## 3           Semantic_Sensitivity 1, 64.87  0.00   .991
## 4 Base_Frequency:Family_Size 1, 92.29    1.01   .317
## 5 Base_Frequency:Semantic_Sensitivity 1, 5679.51  0.41   .523
## 6 Family_Size:Semantic_Sensitivity 1, 5679.38  0.32   .569
## 7 Base_Frequency:Family_Size:Semantic_Sensitivity 1, 5679.34  1.03   .310
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
m1 <- anova_model_words$full_model # Extract the lmer model
ranova(m1) # formally test whether adding each random effect improves fit

```

```

## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## response_time ~ Base_Frequency + Family_Size + Semantic_Sensitivity + (1 | SubjID) + (1 | STRING) + Base_Frequency:Family_Size + Base_Frequency
##                  npar logLik   AIC   LRT Df Pr(>Chisq)
## <none>           11 -35810 71642
## (1 | SubjID)    10 -36768 73555 1915.39 1 < 2.2e-16 ***
## (1 | STRING)    10 -35900 71819 179.31 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_words, partial = TRUE)

```

```

## # Effect Size for ANOVA (Type III)
##
## Parameter          | Eta2 (partial) |      95% CI
## -----
## Base_Frequency     |        0.10 | [0.02, 1.00]
## Family_Size        |        0.09 | [0.02, 1.00]
## Semantic_Sensitivity | 1.79e-06 | [0.00, 1.00]
## Base_Frequency:Family_Size | 0.01 | [0.00, 1.00]
## Base_Frequency:Semantic_Sensitivity | 7.20e-05 | [0.00, 1.00]

```

```

|| Family_Size:Semantic_Sensitivity |      5.71e-05 | [0.00, 1.00]
|| Base_Frequency:Family_Size:Semantic_Sensitivity | 1.82e-04 | [0.00, 1.00]
||
|| - One-sided CIs: upper bound fixed at [1.00].
# Compute Marginal (fixed effects only) and Conditional (fixed + random effects) R^2
r2(anova_model_words)

```

```

|| # R2 for Mixed Models
|| Conditional R2: 0.360
|| Marginal R2: 0.011

```

Concise Explanation

Models including random slopes for Base Frequency and Family Size by subject failed to converge or produced singular fits, indicating that the data did not support estimation of these additional variance components. Consequently, we report results from a simpler model with random intercepts for subjects and items (STRING), which converged cleanly and provided stable estimates.

Fuller explanation

We initially attempted to fit a maximal random-effects structure following Barr et al. (2013), including random slopes for Base Frequency and Family Size by subject. However, these models yielded singular fits (zero variance estimates and perfect correlations among random effects). Because such structures can produce unreliable standard errors and inflated Type I error rates, we adopted the maximal non-singular model, containing random intercepts for both subjects and items (STRING). All reported statistics are based on this model.

Brief

(A more complex model including by-subject random slopes failed to converge; results from the non-singular intercept-only model are reported.)

Main Findings

Effect	df	F	p.value
Base_Frequency	1, 92.29	10.15 **	.002
Family_Size	1, 92.30	9.28 **	.003

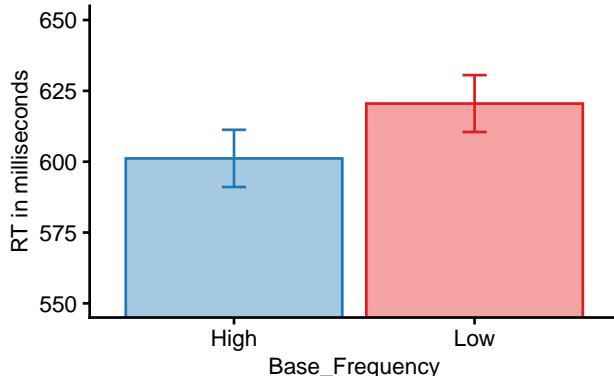
Plots

```

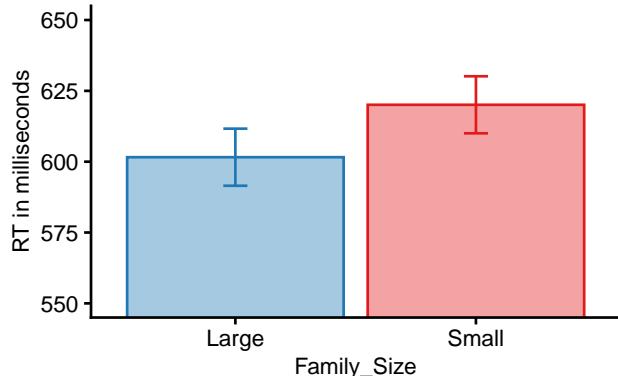
|| Base_Frequency emmean      SE df asymp.LCL asymp.UCL
|| High          601.1588 10.09536 Inf 581.3723 620.9454
|| Low           620.5137 10.04098 Inf 600.8337 640.1936
||
|| Results are averaged over the levels of: Family_Size, Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
||
|| Family_Size emmean      SE df asymp.LCL asymp.UCL
|| Large         601.5859 10.07106 Inf 581.8470 621.3248
|| Small         620.0866 10.06535 Inf 600.3588 639.8143
||
|| Results are averaged over the levels of: Base_Frequency, Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```

A Base Frequency Effect (Words)



B Family Size Effect (Words)



Base_Frequency High Low

Family_Size Large Small

Non-word Data

Use `complete.cases()` to find which rows had missing data in the model-relevant variables:

```
# Specify only the variables used in the model
# model_vars <- c("response_time", "Dim.2", "SubjID")
model_vars_nw <- c("response_time", "Complexity", "Family_Size", "Base_Frequency",
                   "SubjID", "ItemID", "Semantic_Sensitivity")

# Identify incomplete rows
incomplete_cases_nwords <- rt_nwords[!complete.cases(rt_nwords$frq[, model_vars_nw]), ]
rt_nwords_cmpl <- rt_nwords$frq[complete.cases(rt_nwords$frq[, model_vars_nw]), ]
# View them
print(incomplete_cases_nwords)

# str(rt_nwords_1_cmpl)
```

Standardize the predictors

```
rt_nwords_cmpl$LogBF_std <- as.numeric(scale(rt_nwords_cmpl$LogBF, center = TRUE, scale = TRUE))
rt_nwords_cmpl$FS_std <- as.numeric(scale(rt_nwords_cmpl$FS, center = TRUE, scale = TRUE))
rt_nwords_cmpl$BF_std <- as.numeric(scale(rt_nwords_cmpl$BF, center = TRUE, scale = TRUE))
rt_nwords_cmpl$Dim.2_std <- as.numeric(scale(rt_nwords_cmpl$Dim.2, center = TRUE, scale = TRUE))
```

Anova Family Size

```
rt_nwords_cmpl %>%
  count(Complexity, Base_Frequency, Semantic_Sensitivity)

## # A tibble: 8 x 4
##   Complexity Base_Frequency Semantic_Sensitivity     n
##   <chr>      <chr>          <chr>            <int>
## 1 Complex    High           High             504
## 2 Complex    High           Low              402
## 3 Complex    Low            High             595
## 4 Complex    Low            Low              480
## 5 Simple     High           High             702
## 6 Simple     High           Low              565
## 7 Simple     Low            High             719
## 8 Simple     Low            Low              640

temp <- rt_nwords_cmpl |> filter(is.na(Complexity) & is.na(Base_Frequency))
# write_csv(temp, "temp.csv")

anova_model_nwords_fs <- mixed(
  response_time ~ Complexity * Family_Size * Semantic_Sensitivity +
  (1 | SubjID) +
  (1 | ItemID),
  data = rt_nwords_cmpl,
  method = "S")
anova_model_nwords_fs

## Mixed Model Anova Table (Type 3 tests, S-method)
##
## Model: response_time ~ Complexity * Family_Size * Semantic_Sensitivity +
## Model:   (1 | SubjID) + (1 | ItemID)
## Data: rt_nwords_cmpl
## 
##          Effect        df          F p.value
## 1          Complexity 1, 4528.29 122.09 *** <.001
## 2          Family_Size 1, 94.56   0.96   .329
## 3          Semantic_Sensitivity 1, 63.44   0.00   .954
## 4          Complexity:Family_Size 1, 4524.76   0.47   .493
## 5          Complexity:Semantic_Sensitivity 1, 4444.26   0.16   .692
## 6          Family_Size:Semantic_Sensitivity 1, 4442.43   0.17   .678
## 7 Complexity:Family_Size:Semantic_Sensitivity 1, 4442.85   4.84 *  .028
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
m2 <- anova_model_nwords_fs$full_model  # Extract the lmer model
ranova(m2) # Run random effects comparison

## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## response_time ~ Complexity + Family_Size + Semantic_Sensitivity + (1 | SubjID) + (1 | ItemID) + Complexity:Family_Size + Complexity:Semantic_Sensitivity
##          npar logLik   AIC    LRT Df Pr(>Chisq)
## <none>      11 -28034 56090
## (1 | SubjID) 10 -28903 57825 1737.56 1 < 2.2e-16 ***
## (1 | ItemID) 10 -28105 56230 142.56 1 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Main Findings

Effect	df	F	p.value
Complexity	1, 4528.29	122.09 ***	<.001
Family_Size	1, 94.56	0.96	.329
Semantic_Sensitivity	1, 63.44	0.00	.954
Complexity:Family_Size:Semantic_Sensitivity	1, 4442.85	4.84 *	.028

Interaction Effects

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 \times 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 x complexity interaction
(emmm2 <- emmeans(anova_model_nwords_fs, ~ Semantic_Sensitivity * Family_Size * Complexity))
```

```
|| Semantic_Sensitivity Family_Size Complexity emmean    SE df asymp.LCL asymp.UCL
|| High           Large   Complex     742 16.2 Inf   711      774
|| Low            Large   Complex     734 16.6 Inf   702      767
|| High           Small   Complex     726 16.2 Inf   694      758
|| Low            Small   Complex     734 16.6 Inf   702      767
|| High           Large   Simple     698 16.1 Inf   666      729
|| Low            Large   Simple     706 16.4 Inf   673      738
|| High           Small   Simple     699 16.0 Inf   668      731
|| Low            Small   Simple     696 16.3 Inf   664      728
||

|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
# Get all pairwise contrasts
emm2_contrasts <- contrast(emmm2, 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 Large Complex - High Large Simple",
          "High Small Complex - High Small Simple",
          "Low Large Complex - Low Large Simple",
          "Low Small Complex - Low Small Simple",
          "High Large Complex - High Small Complex",
          "High Large Simple - High Small Simple",
          "Low Large Complex - Low Small Complex",
          "Low Large Simple - Low Small Simple",
          "High Large Complex - Low Large Complex",
          "High Small Complex - Low Small Complex",
          "High Large Simple - Low Small Simple",
          "High Small Simple - Low Small Simple")
```

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

```
|| contrast              estimate    SE df z.ratio p.value
|| High Large Complex - Low Large Complex    7.974 22.60 Inf  0.353  0.7239
|| High Large Complex - High Small Complex  16.270 8.25 Inf  1.973  0.0485
|| High Large Complex - High Large Simple  44.698 5.97 Inf  7.484 <.0001
|| Low Large Complex - Low Small Complex   0.216 8.83 Inf  0.024  0.9805
|| Low Large Complex - Low Large Simple   28.755 6.63 Inf  4.339 <.0001
|| High Small Complex - Low Small Complex -8.080 22.50 Inf -0.359  0.7197
|| High Small Complex - High Small Simple  26.910 5.80 Inf  4.641 <.0001
|| Low Small Complex - Low Small Simple   37.975 6.37 Inf  5.966 <.0001
|| High Large Simple - High Small Simple -1.519 7.67 Inf -0.198  0.8430
|| High Large Simple - Low Small Simple   1.466 22.90 Inf  0.064  0.9490
|| Low Large Simple - Low Small Simple    9.435 8.01 Inf  1.177  0.2391
|| High Small Simple - Low Small Simple   2.985 22.30 Inf  0.134  0.8933
||

|| Degrees-of-freedom method: asymptotic
# Get Confidence Intervals
(emmm2_contrasts_filtered_ci <- confint(emmm2_contrasts_filtered))
```

```
|| contrast              estimate    SE df asymp.LCL asymp.UCL
|| High Large Complex - Low Large Complex    7.974 22.60 Inf  -36.261   52.2
|| High Large Complex - High Small Complex  16.270 8.25 Inf   0.106   32.4
```

```

|| High Large Complex - High Large Simple    44.698  5.97 Inf   32.992    56.4
|| Low Large Complex - Low Small Complex     0.216   8.83 Inf  -17.081    17.5
|| Low Large Complex - Low Large Simple     28.755  6.63 Inf   15.766    41.7
|| High Small Complex - Low Small Complex   -8.080  22.50 Inf  -52.202    36.0
|| High Small Complex - High Small Simple   26.910  5.80 Inf   15.545    38.3
|| Low Small Complex - Low Small Simple     37.975  6.37 Inf   25.499    50.5
|| High Large Simple - High Small Simple   -1.519   7.67 Inf  -16.550    13.5
|| High Large Simple - Low Small Simple     1.466   22.90 Inf  -43.475    46.4
|| Low Large Simple - Low Small Simple      9.435   8.01 Inf  -6.273    25.1
|| High Small Simple - Low Small Simple     2.985  22.30 Inf  -40.637    46.6
||
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
# 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 asymp.LCL asymp.UCL
|| High Large Complex - Low Large Complex 0.07804 0.2210 Inf -0.35489  0.511
|| High Large Complex - High Small Complex 0.15923 0.0807 Inf  0.00101  0.317
|| High Large Complex - High Large Simple 0.43747 0.0586 Inf  0.32255  0.552
|| Low Large Complex - Low Small Complex  0.00211 0.0864 Inf -0.16717  0.171
|| Low Large Complex - Low Large Simple  0.28143 0.0649 Inf  0.15417  0.409
|| High Small Complex - Low Small Complex -0.07908 0.2200 Inf -0.51091  0.353
|| High Small Complex - High Small Simple 0.26337 0.0568 Inf  0.15201  0.375
|| Low Small Complex - Low Small Simple   0.37166 0.0624 Inf  0.24933  0.494
|| High Large Simple - High Small Simple -0.01486 0.0751 Inf -0.16197  0.132
|| High Large Simple - Low Small Simple   0.01435 0.2240 Inf -0.42550  0.454
|| Low Large Simple - Low Small Simple    0.09234 0.0784 Inf -0.06140  0.246
|| High Small Simple - Low Small Simple   0.02922 0.2180 Inf -0.39772  0.456
||
|| sigma used for effect sizes: 102.2
|| Degrees-of-freedom method: inherited from asymptotic when re-gridding
|| Confidence level used: 0.95

```

Interaction Contrasts

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

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

```

# 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 z.ratio p.value
|| High - Low                   Large - Small           Complex - Simple        27 12.3 Inf  2.199  0.0279
||
|| Degrees-of-freedom method: asymptotic
confint(contrast(emm2, interaction = c("pairwise", "pairwise")))

|| Semantic_Sensitivity_pairwise Family_Size_pairwise Complexity_pairwise estimate  SE  df asymp.LCL asymp.UCL
|| High - Low                   Large - Small           Complex - Simple        27 12.3 Inf   2.94    51.1
||
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
# Compute the A1 - A2 difference within each combination of B × C
(complexity_diff <- contrast(emm2, method = "repairwise",
                                by = c("Semantic_Sensitivity", "Family_Size"),
                                simple = "Complexity"))

|| Semantic_Sensitivity = High, Family_Size = Large:
|| contrast          estimate  SE  df z.ratio p.value
|| Simple - Complex -44.7  5.97 Inf  -7.484 <.0001
||
|| Semantic_Sensitivity = Low, Family_Size = Large:
|| contrast          estimate  SE  df z.ratio p.value
|| Simple - Complex -28.8  6.63 Inf  -4.339 <.0001
||
|| Semantic_Sensitivity = High, Family_Size = Small:
|| contrast          estimate  SE  df z.ratio p.value
|| Simple - Complex -26.9  5.80 Inf  -4.641 <.0001
||
|| Semantic_Sensitivity = Low, Family_Size = Small:
|| contrast          estimate  SE  df z.ratio p.value

```

```

|| Simple - Complex    -38.0 6.37 Inf  -5.966 <.0001
||
|| Degrees-of-freedom method: asymptotic
# 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 = Simple - Complex, Semantic_Sensitivity = High:
|| contrast1   estimate   SE df z.ratio p.value
|| Small - Large    17.79 8.32 Inf   2.139  0.0325
||
|| contrast = Simple - Complex, Semantic_Sensitivity = Low:
|| contrast1   estimate   SE df z.ratio p.value
|| Small - Large   -9.22 9.18 Inf  -1.004  0.3152
||
|| Degrees-of-freedom method: asymptotic
# Get confidence intervals
confint(family_size_complexity_int_within_sensitivity)

|| contrast = Simple - Complex, Semantic_Sensitivity = High:
|| contrast1   estimate   SE df asymp.LCL asymp.UCL
|| Small - Large    17.79 8.32 Inf      1.49     34.09
||
|| contrast = Simple - Complex, Semantic_Sensitivity = Low:
|| contrast1   estimate   SE df asymp.LCL asymp.UCL
|| Small - Large   -9.22 9.18 Inf   -27.21     8.77
||
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```

Responses were slower to *Complex* than *Simple* nonwords in every condition. The *Complexity effect (Complex - Simple)* varied with both *Family Size* and *Semantic Sensitivity*.

The Complexity effect (slower responses for complex vs. simple nonwords) is robust across all groups.

However, its magnitude varies:

- Among **high-sensitivity participants**, the effect is larger for large families (≈ 45 ms) than small families (≈ 27 ms).
- Among **low-sensitivity participants**, the pattern reverses slightly (≈ 29 ms vs. 38 ms).

The difference in the Complexity \times Family Size interaction between high- and low-sensitivity participants is about 27 ms.

- **High-sensitivity participants** showed a stronger complexity effect for large-family nonwords than for small-family ones.
- **Low-sensitivity participants** showed the opposite or no difference.

This indicates that semantic sensitivity modulates how morphological family size influences the cost of morphological complexity in nonword processing.

All groups show reliable complexity effects (complex slower than simple). Only one cross-condition difference is significant: High-sensitivity participants respond faster to complex nonwords from small families than to complex nonwords from large-families.

Summary interpretation (for Results section):

Response times to morphologically complex nonwords were significantly slower than to simple nonwords, indicating greater processing cost for complexity. While overall family size and semantic sensitivity did not produce main effects, there was a significant Complexity \times Family Size \times Semantic Sensitivity interaction ($p = .028$).

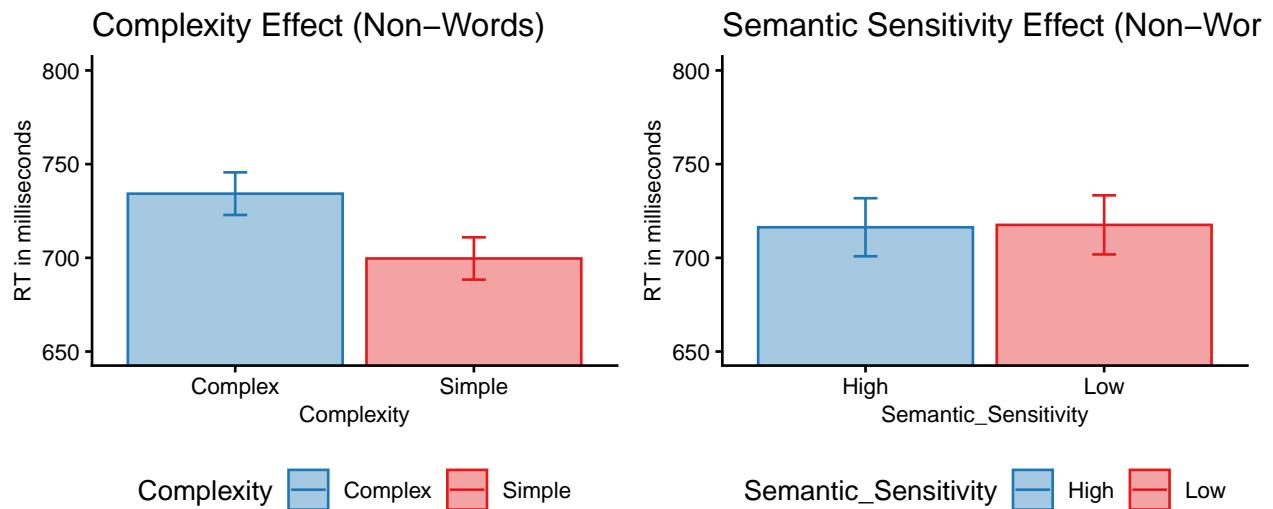
Follow-up contrasts showed that for participants with high semantic sensitivity, the complexity effect was larger for large-family nonwords (≈ 45 ms) than for small-family nonwords (≈ 27 ms). In contrast, participants with low semantic sensitivity showed little difference or the reverse pattern. This suggests that individuals with greater semantic knowledge are more sensitive to morphological family size cues when processing novel morphological structures, showing amplified complexity costs when nonwords resemble rich morphological families.

Plots

```

|| Complexity   emmean      SE df asymp.LCL asymp.UCL
|| Complex      734.2425 11.3619 Inf  711.9736 756.5114
|| Simple       699.6580 11.2898 Inf  677.5304 721.7855
||
|| Results are averaged over the levels of: Family_Size, Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
||
|| Semantic_Sensitivity   emmean      SE df asymp.LCL asymp.UCL
|| High                  716.3141 15.49217 Inf  685.9500 746.6782
|| Low                   717.5864 15.76981 Inf  686.6782 748.4947
||
|| Results are averaged over the levels of: Complexity, Family_Size
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```



Anova Base Frequency

```

anova_model_nwords_bf <- mixed(
  response_time ~ Complexity * Base_Frequency * Semantic_Sensitivity +
  (1 | SubjID) +
  (1 | ItemID),
  data = rt_nwords_cmpl,
  method = "S")
anova_model_nwords_bf

## Mixed Model Anova Table (Type 3 tests, S-method)
##
## Model: response_time ~ Complexity * Base_Frequency * Semantic_Sensitivity +
## Model:      (1 | SubjID) + (1 | ItemID)
## Data: rt_nwords_cmpl
##          Effect      df       F p.value
## 1           Complexity 1, 4533.26 125.15 *** <.001
## 2           Base_Frequency 1, 95.24 12.70 *** <.001
## 3           Semantic_Sensitivity 1, 63.45 0.00 .968
## 4 Complexity:Base_Frequency 1, 4535.00 3.92 * .048
## 5 Complexity:Semantic_Sensitivity 1, 4446.84 0.21 .647
## 6 Base_Frequency:Semantic_Sensitivity 1, 4445.63 1.15 .284
## 7 Complexity:Base_Frequency:Semantic_Sensitivity 1, 4446.76 2.56 .110
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
m3 <- anova_model_nwords_bf$full_model    # Extract the lmer model
ranova(m3) # Run random effects comparison

## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## response_time ~ Complexity + Base_Frequency + Semantic_Sensitivity + (1 | SubjID) + (1 | ItemID) + Complexity:Base_Frequency + Complexity:Semantic_Sensitivity
##          npar logLik AIC      LRT Df Pr(>Chisq)
## <none>      11 -28028 56077
## (1 | SubjID) 10 -28897 57815 1739.59 1 < 2.2e-16 ***
## (1 | ItemID) 10 -28089 56197 122.45 1 < 2.2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1

```

Main Findings

Effect	df	F	p.value
Complexity	1, 4533.26	125.15 ***	<.001
Base_Frequency	1, 95.24	12.70 **	<.001
Complexity:Base_Frequency	1, 4535.47	3.92 *	.048

Participants responded more slowly to complex nonwords and to low-frequency-base nonwords.

Interaction Effects: Complexity x Base Frequency

```
# Estimated marginal means for the family_size x base frequency interaction
(emm1 <- emmeans(anova_model_nwords_bf, ~ Complexity * Base_Frequency))
```

Simple Contrasts

```

## Complexity Base_Frequency emmean   SE df asymp.LCL asymp.UCL
## Complex  High        748 11.9 Inf   725    772
## Simple   High        707 11.7 Inf   684    730
## Complex  Low         721 11.8 Inf   698    744
## Simple   Low         692 11.7 Inf   669    715
##
## Results are averaged over the levels of: Semantic_Sensitivity
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
# Get all pairwise contrasts
emm1_contrasts <- contrast(emm1, method = "pairwise", by = NULL, adjust = "none")
emm1_contrasts
```

```

## contrast            estimate   SE df z.ratio p.value
## Complex High - Simple High  41.3 4.63 Inf  8.915 <.0001
## Complex High - Complex Low 27.3 6.93 Inf  3.945 0.0001
## Complex High - Simple Low  56.2 6.76 Inf  8.319 <.0001
## Simple High - Complex Low -14.0 6.66 Inf -2.099 0.0359
## Simple High - Simple Low   14.9 6.48 Inf  2.298 0.0216
## Complex Low - Simple Low   28.9 4.24 Inf  6.800 <.0001
```

```

|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
# Keep only the contrasts you want
# Simple effects of Complexity at each level of Base_Frequency
# Simple effects of Base_Frequency at each level of Complexity
keep <- c("Complex High - Simple High",
        "Complex Low - Simple Low",
        "Complex High - Complex Low",
        "Simple High - Simple Low")
(emm1_contrasts_filtered <- subset(emm1_contrasts, contrast %in% keep))

|| contrast estimate SE df z.ratio p.value
|| Complex High - Simple High 41.3 4.63 Inf 8.915 <.0001
|| Complex High - Complex Low 27.3 6.93 Inf 3.945 0.0001
|| Simple High - Simple Low 14.9 6.48 Inf 2.298 0.0216
|| Complex Low - Simple Low 28.9 4.24 Inf 6.800 <.0001
||

|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
# Get Confidence Intervals
(emm1_contrasts_filtered_ci <- confint(emm1_contrasts_filtered))

|| contrast estimate SE df asymp.LCL asymp.UCL
|| Complex High - Simple High 41.3 4.63 Inf 32.23 50.4
|| Complex High - Complex Low 27.3 6.93 Inf 13.76 40.9
|| Simple High - Simple Low 14.9 6.48 Inf 2.19 27.6
|| Complex Low - Simple Low 28.9 4.24 Inf 20.54 37.2
||

|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
# Get effect sizes
# Get all pairwise effect sizes
effs1 <- eff_size(emm1, sigma = sigma(m3), edf = df.residual(m3))
effs1

|| contrast effect.size SE df asymp.LCL asymp.UCL
|| Complex High - Simple High 0.405 0.0456 Inf 0.3152 0.494
|| Complex High - Complex Low 0.268 0.0679 Inf 0.1346 0.401
|| Complex High - Simple Low 0.550 0.0664 Inf 0.4202 0.681
|| Simple High - Complex Low -0.137 0.0652 Inf -0.2645 -0.009
|| Simple High - Simple Low 0.146 0.0635 Inf 0.0214 0.270
|| Complex Low - Simple Low 0.283 0.0417 Inf 0.2009 0.364
||

|| Results are averaged over the levels of: Semantic_Sensitivity
|| sigma used for effect sizes: 102.1
|| Degrees-of-freedom method: inherited from asymptotic when re-gridding
|| Confidence level used: 0.95
# Remove the two redundant rows (rows 3 and 4)
(emm1_filtered <- subset(emm1, !contrast %in% c("Complex High - Simple Low",
                                                 "Simple High - Complex Low")))

|| contrast effect.size SE df asymp.LCL asymp.UCL
|| Complex High - Simple High 0.405 0.0456 Inf 0.3152 0.494
|| Complex High - Complex Low 0.268 0.0679 Inf 0.1346 0.401
|| Simple High - Simple Low 0.146 0.0635 Inf 0.0214 0.270
|| Complex Low - Simple Low 0.283 0.0417 Inf 0.2009 0.364
||

|| Results are averaged over the levels of: Semantic_Sensitivity
|| sigma used for effect sizes: 102.1
|| Degrees-of-freedom method: inherited from asymptotic when re-gridding
|| Confidence level used: 0.95

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

```

Interaction Contrasts

```

|| Complexity_pairwise Base_Frequency_pairwise estimate SE df z.ratio p.value
|| Complex - Simple     High - Low             12.5 6.3 Inf 1.979 0.0479
||

|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
# Get confidence intervals, for each base frequency effect for each family size and then for interaction effect
confint(contrast(emmeans(m3, ~ Complexity | Base_Frequency), "pairwise"))

```

```

|| Base_Frequency = High:
|| contrast estimate SE df asymp.LCL asymp.UCL
|| Complex - Simple 41.3 4.63 Inf 32.2 50.4
||
|| Base_Frequency = Low:
|| contrast estimate SE df asymp.LCL asymp.UCL
|| Complex - Simple 28.9 4.24 Inf 20.5 37.2
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
confint(contrast(emm1, interaction = c("pairwise", "pairwise")))

|| Complexity_pairwise Base_Frequency_pairwise estimate SE df asymp.LCL asymp.UCL
|| Complex - Simple High - Low 12.5 6.3 Inf 0.118 24.8
||
|| Results are averaged over the levels of: Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```

A small but reliable Complexity \times Base Frequency interaction ($p = .048$) suggests that the complexity cost was smaller for nonwords derived from low-frequency bases.

Complexity	Base Frequency	Mean RT (ms)	Interpretation
Complex	High	748	slowest
Simple	High	707	41 ms faster
Complex	Low	721	28 ms slower than Simple Low
Simple	Low	692	fastest

Both complexity and base frequency affect RTs additively, but their combination reveals that high-frequency bases magnify the complexity cost.

- The complexity effect (Complex – Simple) is larger for *high-frequency* bases (41 ms) than for *low-frequency* ones (29 ms).
- The base-frequency advantage (High – Low) is stronger for *complex* items (27 ms) than for *simple* ones (15 ms).
- Both effects are moderate in size (Cohen's $d \approx 0.3^{\circ}0.4$).

The complexity cost increases by about 12 ms when the base is high frequency rather than low frequency, confirming the small but significant interaction.

No effects involving Semantic Sensitivity were observed, indicating that this base-frequency modulation of complexity applies broadly across participants, independent of their semantic knowledge.

Main Effects Plots

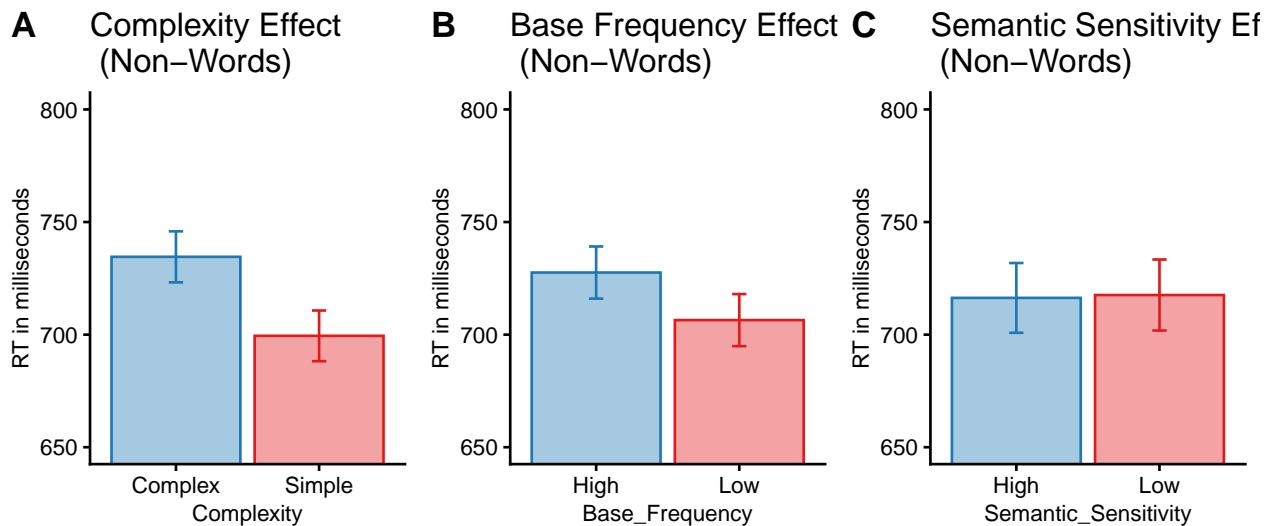
```

|| Complexity emmean SE df asymp.LCL asymp.UCL
|| Complex 734.5516 11.32891 Inf 712.3473 756.7559
|| Simple 699.4623 11.25555 Inf 677.4018 721.5227
||
|| Results are averaged over the levels of: Base_Frequency, Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

|| Base_Frequency emmean SE df asymp.LCL asymp.UCL
|| High 727.5677 11.57476 Inf 704.8815 750.2538
|| Low 706.4462 11.56316 Inf 683.7828 729.1096
||
|| Results are averaged over the levels of: Complexity, Semantic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

|| Semantic_Sensitivity emmean SE df asymp.LCL asymp.UCL
|| High 716.5652 15.47076 Inf 686.2431 746.8874
|| Low 717.4486 15.74909 Inf 686.5810 748.3163
||
|| Results are averaged over the levels of: Complexity, Base_Frequency
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```



Interaction Plots

```
p8 <- emmip(anova_model_nwords_bf, Complexity ~ Base_Frequency) + my_style
p9 <- emmip(anova_model_nwords_bf, Base_Frequency ~ Complexity) + my_style
```

```
plot_grid(p8, p9, ncol = 2)
```

