

# M21 RT Orthographic 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$Orthographic_Sensitivity[rt_words_frq$Orthographic_Sensitivity == "Low"] <- "Low Sensitivity"
# rt_words_frq$Orthographic_Sensitivity[rt_words_frq$Orthographic_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", "Orthographic_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 * Orthographic_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 * Orthographic_Sensitivity +
|| Model:      (1 | SubjID) + (1 | STRING)
|| Data: rt_words_cmpl
||                               Effect          df     F p.value
|| 1                         Base_Frequency 1, 92.45 10.29 **   .002
|| 2                         Family_Size   1, 92.44  9.41 **   .003
|| 3                         Orthographic_Sensitivity 1, 64.87  3.83 +   .055
|| 4                         Base_Frequency:Family_Size 1, 92.45   1.08   .300
|| 5                         Base_Frequency:Orthographic_Sensitivity 1, 5682.28   0.05   .817
|| 6                         Family_Size:Orthographic_Sensitivity 1, 5682.26   0.06   .809
|| 7                         Base_Frequency:Family_Size:Orthographic_Sensitivity 1, 5682.09   0.16   .691
|| ---
|| 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 + Orthographic_Sensitivity + (1 | SubjID) + (1 | STRING) + Base_Frequency:Family_Size + Base_Freq
||                               npar logLik   AIC     LRT Df Pr(>Chisq)
|| <none>                  11 -35809 71639
|| (1 | SubjID)      10 -36718 73455 1817.77  1 < 2.2e-16 ***
|| (1 | STRING)       10 -35899 71817 179.65  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]
|| Orthographic_Sensitivity |        0.06 | [0.00, 1.00]
|| Base_Frequency:Family_Size |        0.01 | [0.00, 1.00]
|| Base_Frequency:Orthographic_Sensitivity | 9.41e-06 | [0.00, 1.00]

```

```

|| Family_Size:Orthographic_Sensitivity |      1.03e-05 | [0.00, 1.00]
|| Base_Frequency:Family_Size:Orthographic_Sensitivity |      2.78e-05 | [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: 0.028

```

Concise

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 Effects

Effect	df	F	p.value
Base_Frequency	1, 92.45	10.29 **	.002
Family_Size	1, 92.44	9.41 **	.003

```
emmeans(anova_model_words, ~ Family_Size)
```

## Means

```

|| Family_Size emmean   SE  df asymp.LCL asymp.UCL
|| Large          603 9.86 Inf    584     622
|| Small          622 9.85 Inf    602     641
||
|| Results are averaged over the levels of: Base_Frequency, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
emmeans(anova_model_words, ~ Base_Frequency)

```

```

|| Base_Frequency emmean   SE  df asymp.LCL asymp.UCL
|| High            602 9.88 Inf    583     622
|| Low             622 9.83 Inf    603     641
||
|| Results are averaged over the levels of: Family_Size, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
emmeans(anova_model_words, ~ Orthographic_Sensitivity)

```

```

|| Orthographic_Sensitivity emmean   SE  df asymp.LCL asymp.UCL
|| High              595 12.5 Inf    570     619
|| Low               630 13.4 Inf    603     656
||
|| Results are averaged over the levels of: Base_Frequency, Family_Size
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```

## Plots

```

|| Base_Frequency emmean       SE  df asymp.LCL asymp.UCL
|| High           602.4149 9.881996 Inf  583.0465 621.7832
|| Low            621.9280 9.826032 Inf  602.6694 641.1867
||
|| Results are averaged over the levels of: Family_Size, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

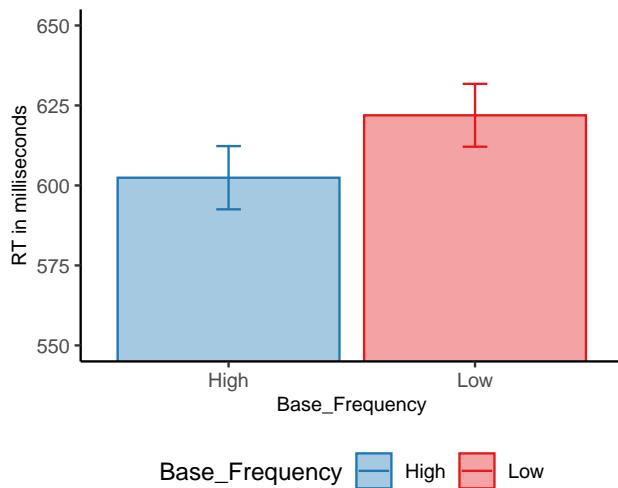
```

```

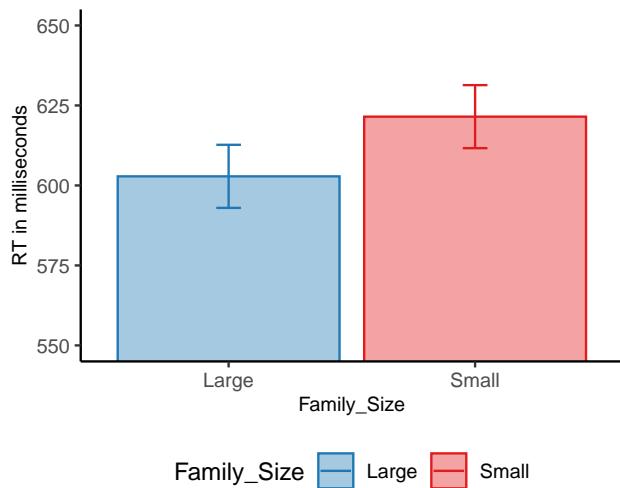
|| Family_Size      emmean       SE  df asymp.LCL asymp.UCL
|| Large           602.8423 9.856568 Inf  583.5238 622.1608
|| Small           621.5006 9.851504 Inf  602.1920 640.8092
||
|| Results are averaged over the levels of: Base_Frequency, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```

**A** Base Frequency Effect (Words)



**B** Family Size Effect (Words)



## Non-word Data

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

```
## 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

```
anova_model_nwords_fs <- mixed(
  response_time ~ Complexity * Family_Size * Orthographic_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 * Orthographic_Sensitivity +
## Model:   (1 | SubjID) + (1 | ItemID)
## Data: rt_nwords_cmpl
##          Effect      df        F p.value
## 1            Complexity 1, 4529.58 124.76 *** <.001
## 2            Family_Size 1, 95.23   1.10   .297
## 3            Orthographic_Sensitivity 1, 63.59   5.37 * .024
## 4            Complexity:Family_Size 1, 4525.57   0.92   .338
## 5            Complexity:Orthographic_Sensitivity 1, 4512.75   0.96   .327
## 6            Family_Size:Orthographic_Sensitivity 1, 4448.54   0.09   .770
## 7            Complexity:Family_Size:Orthographic_Sensitivity 1, 4508.97   0.06   .809
## ---
## 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 + Orthographic_Sensitivity + (1 | SubjID) + (1 | ItemID) + Complexity:Family_Size + Complexity:Orthogr
##          npar logLik     AIC      LRT Df Pr(>Chisq)
## <none>       11 -28033 56089
## (1 | SubjID) 10 -28862 57743 1656.71 1 < 2.2e-16 ***
## (1 | ItemID) 10 -28105 56230 142.95 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_nwords_fs, partial = TRUE)

## # Effect Size for ANOVA (Type III)
##
## Parameter          | Eta2 (partial) |      95% CI
## -----
## Complexity          |      0.03 | [0.02, 1.00]
## Family_Size         |      0.01 | [0.00, 1.00]
## Orthographic_Sensitivity | 0.08 | [0.01, 1.00]
## Complexity:Family_Size | 2.03e-04 | [0.00, 1.00]
## Complexity:Orthographic_Sensitivity | 2.12e-04 | [0.00, 1.00]
## Family_Size:Orthographic_Sensitivity | 1.92e-05 | [0.00, 1.00]
## Complexity:Family_Size:Orthographic_Sensitivity | 1.29e-05 | [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_nwords_fs)

## # R2 for Mixed Models
##
## Conditional R2: 0.456
## Marginal R2: 0.045
```

## Main Effects

Effect	df	F	p.value
Complexity	1, 4529.58	124.76 ***	<.001
Orthographic_Sensitivity	1, 63.59	5.37 *	.024

```
emmeans(anova_model_nwords_fs, ~ Complexity)
```

### Main Effects Means

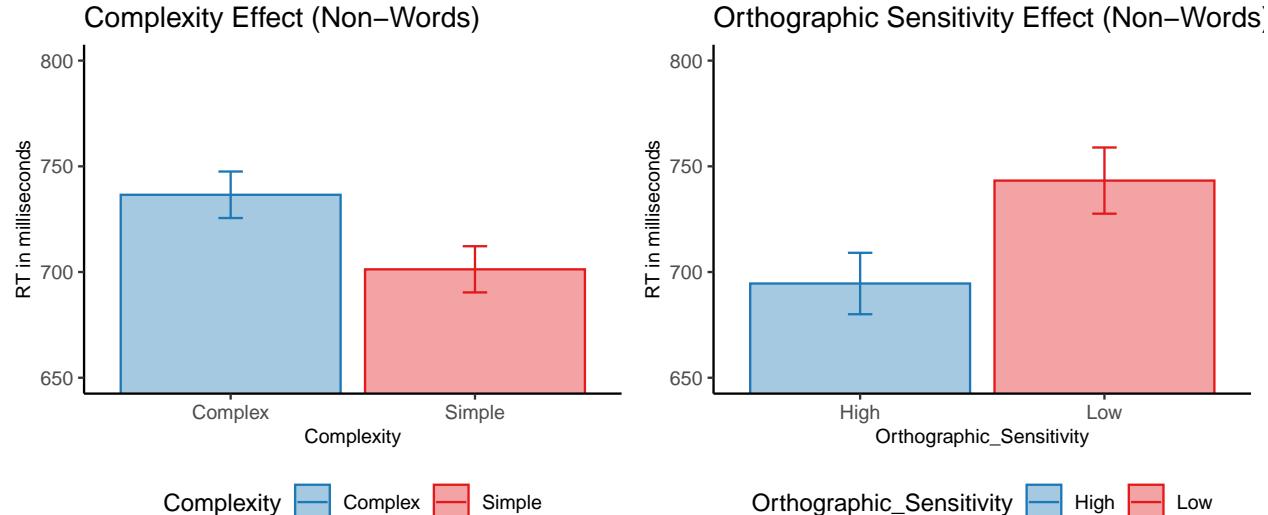
```
|| Complexity emmean SE df asymp.LCL asymp.UCL
|| Complex      737 11.0 Inf     715     758
|| Simple       701 10.9 Inf     680     723
||
|| Results are averaged over the levels of: Family_Size, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
emmeans(anova_model_nwords_fs, ~ Family_Size)

|| Family_Size emmean SE df asymp.LCL asymp.UCL
|| Large        722 11.3 Inf     700     744
|| Small        716 11.3 Inf     694     738
||
|| Results are averaged over the levels of: Complexity, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
emmeans(anova_model_nwords_fs, ~ Orthographic_Sensitivity)

|| Orthographic_Sensitivity emmean SE df asymp.LCL asymp.UCL
|| High          695 14.5 Inf     666     723
|| Low           743 15.7 Inf     713     774
||
|| Results are averaged over the levels of: Complexity, Family_Size
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
```

**Non-word complexity** had a robust effect; complex non-words (e.g., pseudoderived forms) elicited longer response times than simple ones. Participants with higher **orthographic sensitivity** responded significantly faster overall, suggesting more efficient processing of letter patterns even in non-words. **Morphological family size** did not modulate non-word RTs, nor did it interact with complexity or orthographic sensitivity. Interpretation: In the absence of lexical representations, apparent “family size” (based on real-word analogues) does not measurably influence non-word recognition.

### Main Effects Plots ...



## Anova Base Frequency

```

anova_model_nwords_bf <- mixed(
  response_time ~ Complexity * Base_Frequency * Orthographic_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 * Orthographic_Sensitivity +
## Model:      (1 | SubjID) + (1 | ItemID)
## Data: rt_nwords_cmpl
##                                         Effect      df        F p.value
## 1                               Complexity 1, 4534.35 127.54 ***  <.001
## 2                               Base_Frequency 1, 95.95  12.99 **   <.001
## 3                         Orthographic_Sensitivity 1, 63.60   5.32 *   .024
## 4             Complexity:Base_Frequency 1, 4535.47   4.26 *   .039
## 5       Complexity:Orthographic_Sensitivity 1, 4517.84   0.86   .353
## 6     Base_Frequency:Orthographic_Sensitivity 1, 4452.86   0.04   .838
## 7 Complexity:Base_Frequency:Orthographic_Sensitivity 1, 4515.97   0.35   .555
## ---
## 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 + Orthographic_Sensitivity + (1 | SubjID) + (1 | ItemID) + Complexity:Base_Frequency + Complexity:O
##                                npar logLik   AIC   LRT Df Pr(>Chisq)
## <none>                  11 -28026 56074
## (1 | SubjID)    10 -28857 57734 1662.17 1 < 2.2e-16 ***
## (1 | ItemID)    10 -28087 56195 122.89 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_nwords_bf, partial = TRUE)

## # Effect Size for ANOVA (Type III)
##
## Parameter                      | Eta2 (partial) |      95% CI
## -----
## Complexity                     |      0.03 | [0.02, 1.00]
## Base_Frequency                 |      0.12 | [0.04, 1.00]
## Orthographic_Sensitivity      |      0.08 | [0.01, 1.00]
## Complexity:Base_Frequency    |  9.38e-04 | [0.00, 1.00]
## Complexity:Orthographic_Sensitivity |  1.91e-04 | [0.00, 1.00]
## Base_Frequency:Orthographic_Sensitivity |  9.44e-06 | [0.00, 1.00]
## Complexity:Base_Frequency:Orthographic_Sensitivity |  7.72e-05 | [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_nwords_bf)

## # R2 for Mixed Models
##
## Conditional R2: 0.458
## Marginal R2: 0.050

```

## Main Findings

Effect	df	F	p.value
Complexity	1, 4534.35	127.54 ***	<.001
Base_Frequency	1, 177.77	12.99 **	<.001
Orthographic_Sensitivity	1, 63.60	5.32 *	.024
Complexity:Base_Frequency	1, 4535.47	4.26 *	.039

- Complexity ( $F = 127.5$ ,  $p < .001$ ): complex > simple non-words → slower responses.
- Base Frequency ( $F = 13.0$ ,  $p < .001$ ): non-words derived from high-frequency bases were processed faster than those from low-frequency bases — an echo of lexical familiarity effects even though the items are illegal.
- Orthographic Sensitivity ( $F = 5.32$ ,  $p = .024$ ): same direction as before.

- Complexity × Base Frequency ( $F = 4.26$ ,  $p = .039$ ): The effect of complexity was larger for high-frequency bases than for low-frequency ones.

```

## emmeans(anova_model_nwords_bf, ~ Complexity)

## Complexity emmean   SE  df asymp.LCL asymp.UCL
## Complex      737 11.0 Inf     715     758
## Simple       701 10.9 Inf     680     722
##
## Results are averaged over the levels of: Base_Frequency, Orthographic_Sensitivity
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
## emmeans(anova_model_nwords_bf, ~ Base_Frequency)

## Base_Frequency emmean   SE  df asymp.LCL asymp.UCL
## High          730 11.2 Inf     708     752
## Low           708 11.2 Inf     686     730
##
## Results are averaged over the levels of: Complexity, Orthographic_Sensitivity
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95
## emmeans(anova_model_nwords_bf, ~ Orthographic_Sensitivity)

## Orthographic_Sensitivity emmean   SE  df asymp.LCL asymp.UCL
## High          695 14.5 Inf     666     723
## Low           743 15.7 Inf     713     774
##
## Results are averaged over the levels of: Complexity, Base_Frequency
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95

```

## 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          751 11.6 Inf     728     773
## Simple    High          709 11.4 Inf     686     731
## Complex    Low           723 11.5 Inf     700     745
## Simple    Low           694 11.4 Inf     671     716
##
## Results are averaged over the levels of: Orthographic_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  42.3 4.68 Inf  9.033 <.0001
## Complex High - Complex Low  28.0 6.95 Inf  4.021 0.0001
## Complex High - Simple Low   57.1 6.78 Inf  8.429 <.0001
## Simple High - Complex Low  -14.3 6.69 Inf -2.136 0.0326
## Simple High - Simple Low    14.9 6.51 Inf  2.285 0.0223
## Complex Low - Simple Low   29.2 4.27 Inf  6.834 <.0001
##
## Results are averaged over the levels of: Orthographic_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  42.3 4.68 Inf  9.033 <.0001
## Complex High - Complex Low  28.0 6.95 Inf  4.021 0.0001
## Simple High - Simple Low    14.9 6.51 Inf  2.285 0.0223
## Complex Low - Simple Low   29.2 4.27 Inf  6.834 <.0001
##
## Results are averaged over the levels of: Orthographic_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 42.3 4.68 Inf 33.09 51.4
|| Complex High - Complex Low 28.0 6.95 Inf 14.34 41.6
|| Simple High - Simple Low 14.9 6.51 Inf 2.12 27.6
|| Complex Low - Simple Low 29.2 4.27 Inf 20.81 37.5
||

|| Results are averaged over the levels of: Orthographic_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 0.414 0.0460 Inf 0.3235 0.5038
|| Complex High - Complex Low 0.274 0.0681 Inf 0.1402 0.4073
|| Complex High - Simple Low 0.559 0.0666 Inf 0.4288 0.6899
|| Simple High - Complex Low -0.140 0.0655 Inf -0.2682 -0.0115
|| Simple High - Simple Low 0.146 0.0638 Inf 0.0207 0.2707
|| Complex Low - Simple Low 0.286 0.0419 Inf 0.2035 0.3677
||

|| Results are averaged over the levels of: Orthographic_Sensitivity
|| sigma used for effect sizes: 102.2
|| Degrees-of-freedom method: inherited from asymptotic when re-gridding
|| Confidence level used: 0.95
# Remove the two redundant rows (rows 3 and 4)
(emfs1_filtered <- subset(effs1, !contrast %in% c("Complex High - Simple Low",
"Simple High - Complex Low")))

|| contrast effect.size SE df asymp.LCL asymp.UCL
|| Complex High - Simple High 0.414 0.0460 Inf 0.3235 0.504
|| Complex High - Complex Low 0.274 0.0681 Inf 0.1402 0.407
|| Simple High - Simple Low 0.146 0.0638 Inf 0.0207 0.271
|| Complex Low - Simple Low 0.286 0.0419 Inf 0.2035 0.368
||

|| Results are averaged over the levels of: Orthographic_Sensitivity
|| sigma used for effect sizes: 102.2
|| 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 13.1 6.34 Inf 2.063 0.0391
||

|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
confint(contrast(emm1, interaction = c("pairwise", "pairwise")))

|| Complexity_pairwise Base_Frequency_pairwise estimate SE df asymp.LCL asymp.UCL
|| Complex - Simple High - Low 13.1 6.34 Inf 0.655 25.5
||

|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
# 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 42.3 4.68 Inf 33.1 51.4
||

|| Base_Frequency = Low:
|| contrast estimate SE df asymp.LCL asymp.UCL
|| Complex - Simple 29.2 4.27 Inf 20.8 37.5
||

|| Results are averaged over the levels of: Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95

```

```

confint(contrast(emmeans(m3, ~ Base_Frequency | Complexity), "pairwise"))

## Complexity = Complex:
## contrast estimate SE df asymp.LCL asymp.UCL
## High - Low    28.0 6.95 Inf   14.34     41.6
##
## Complexity = Simple:
## contrast estimate SE df asymp.LCL asymp.UCL
## High - Low    14.9 6.51 Inf    2.12     27.6
##
## Results are averaged over the levels of: Orthographic_Sensitivity
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95

```

Table 4. Estimated Marginal Means and Pairwise Contrasts for the Complexity  $\times$  Base Frequency Interaction

Contrast	Delta RT (ms)	p	Effect size (d)	95% CI for Delta RT (ms)	Interpretation
Complex High (751) - Simple High (709)	+42.3	< .001	0.41	[33.1, 51.4]	Strong complexity cost at high base frequency
Complex Low (723) - Simple Low (694)	+29.2	< .001	0.29	[20.8, 37.5]	Moderate complexity cost at low base frequency
Complex High (751) - Complex Low (723)	+28.0	.0001	0.27	[14.3, 41.6]	Complex items slower when based on high-frequency stems
Simple High (709) - Simple Low (694)	+14.9	.022	0.15	[2.1, 27.6]	Small frequency benefit among simple items

Table 5. Summary of Main Effects and Interactions

Effect	Direction / Pattern	Interpretation
Complexity	Complex > Simple across all conditions	Morphological structure slows non-word rejection (decomposition cost).
Base Frequency	High > Low (faster RTs)	Familiar letter sequences facilitate processing even for non-words.
Complexity $\times$ Base Frequency	Larger complexity cost for high-frequency bases (Delta ~ 13 ms)	Morphological activation stronger for familiar bases.
Family Size	n.s.	No measurable influence; non-words lack real morphological families.
Orthographic Sensitivity	High > Low (faster RTs overall)	Readers with higher orthographic sensitivity are generally more efficient.

## Main Effects Plots

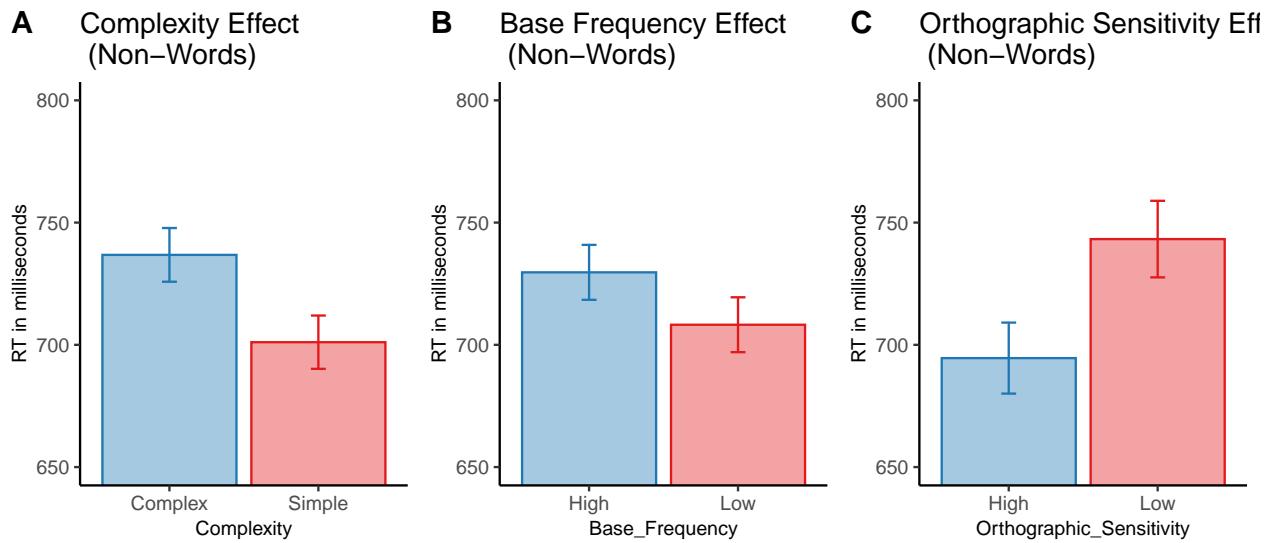
```

## Complexity emmean      SE df asymp.LCL asymp.UCL
## Complex    736.7913 10.98256 Inf  715.2659  758.3168
## Simple     701.0784 10.90537 Inf  679.7042  722.4525
##
## Results are averaged over the levels of: Base_Frequency, Orthographic_Sensitivity
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95

## Base_Frequency emmean      SE df asymp.LCL asymp.UCL
## High        729.6473 11.23700 Inf  707.6232  751.6715
## Low         708.2224 11.22244 Inf  686.2268  730.2180
##
## Results are averaged over the levels of: Complexity, Orthographic_Sensitivity
## Degrees-of-freedom method: asymptotic
## Confidence level used: 0.95

## Orthographic_Sensitivity emmean      SE df asymp.LCL asymp.UCL
## High        694.6539 14.52304 Inf  666.1892  723.1185
## Low         743.2159 15.66167 Inf  712.5196  773.9122
##
## 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)
```

