

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_Frequency:Orthographic_Sensitivity
||      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

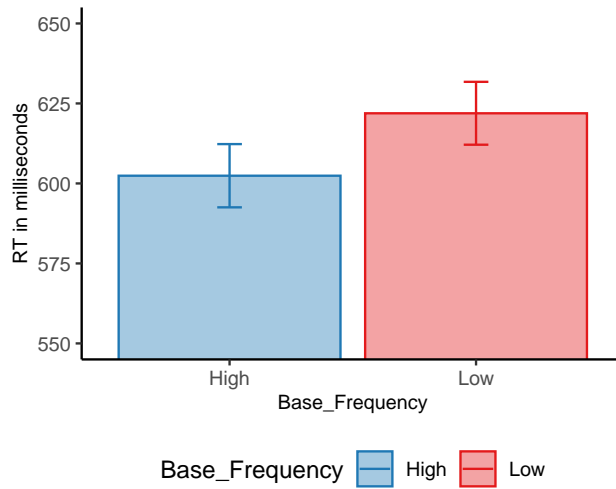
```

```

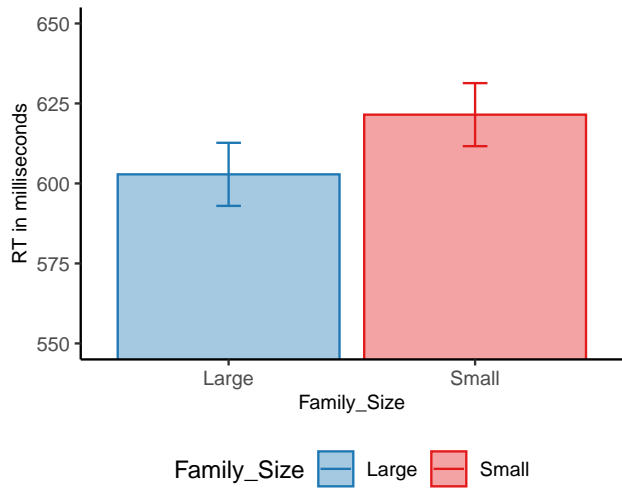
|| Family_Size    emmean      SE  df asymp.LCL asymp.UCL
|| Large         602.8423  9.856568 Inf  583.5238  622.1608
|| Small         621.5006  9.851504 Inf  602.1920  640.8092
||
|| Results are averaged over the levels of: Base_Frequency, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic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

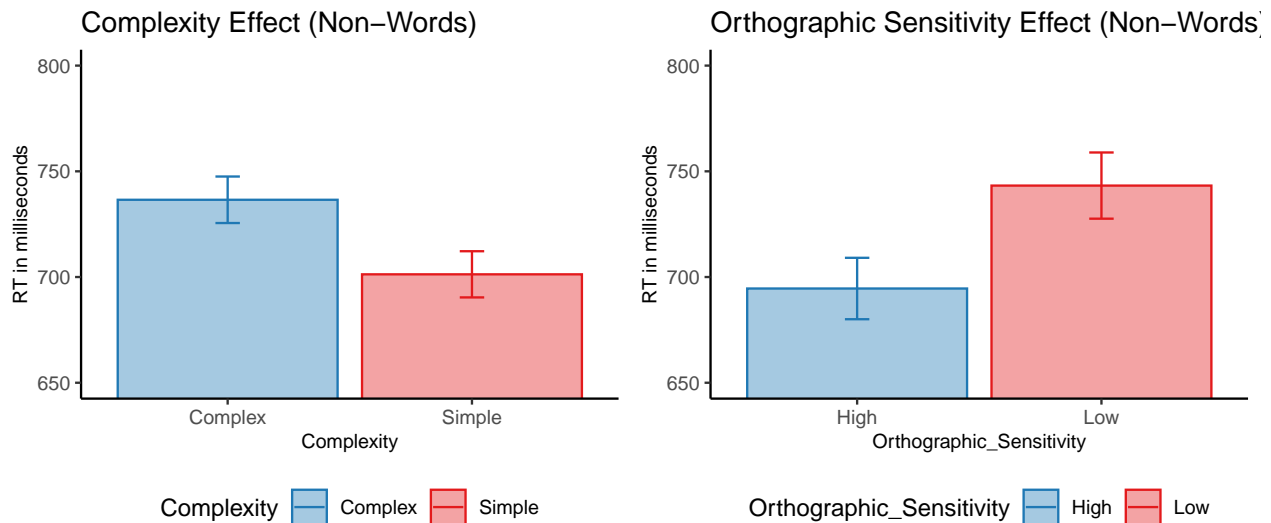
```
|| Family_Size emmean SE df asymp.LCL asymp.UCL
|| Large      722 11.3 Inf      700      744
|| Small      716 11.3 Inf      694      738
||
|| Results are averaged over the levels of: Complexity, Orthographic_Sensitivity
|| Degrees-of-freedom method: asymptotic
|| Confidence level used: 0.95
```

```
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:Orthographic_Sensitivity
||          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) R^2
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 \times 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
(emml1 <- 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
emml1_contrasts <- contrast(emml1, method = "pairwise", by = NULL, adjust = "none")
emml1_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")
(emml1_contrasts_filtered <- subset(emml1_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
(emml_contrasts_filtered_ci <- confint(emml_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(emml, 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)
(effs1_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(emml, 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(emml, 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

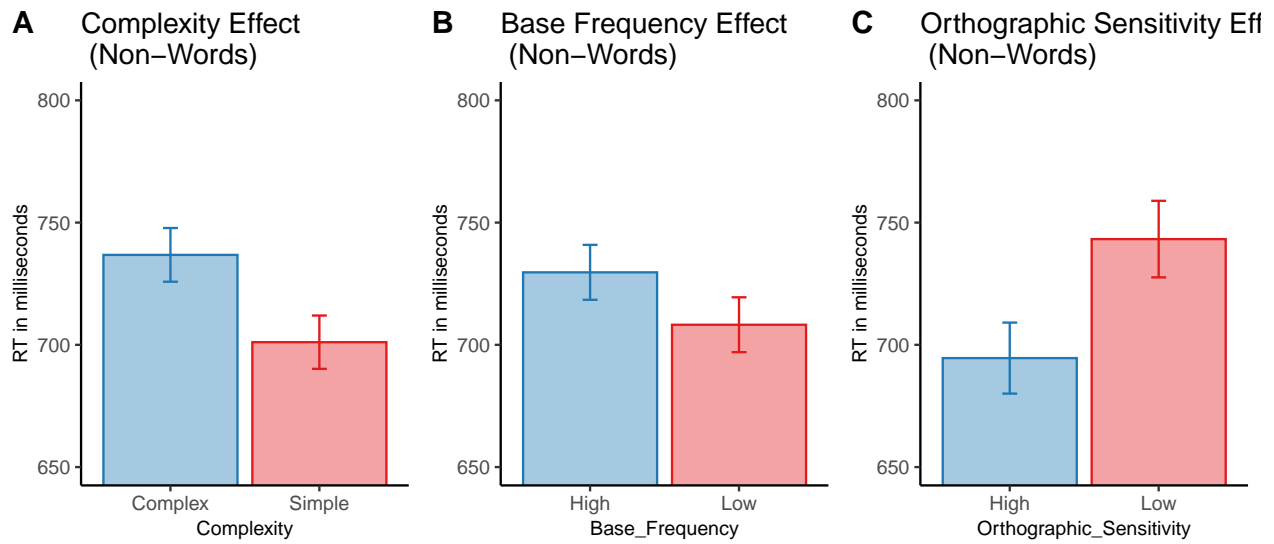
Effect	Direction / Pattern	Interpretation
Complexity	Complex > Simple across all conditions	Morphological structure slows non-word rejection (decomposition cost).
Base Frequency	High > Low (faster RTs)	Familiar letter sequences facilitate processing even for non-words.
Complexity \times Base Frequency	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)
```

