

m21_rt

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Setup

Load libraries

1. Set `ggplot2` parameters

Load Files and Format Files

Load Files

```
rt_1 <- read_csv("rt_data_chrt1.csv")
rt_2 <- read_csv("rt_data_chrt2.csv")
frq_w <- read_csv("stimuli_cw_frq.csv")
frq_nw <- read_csv("frq_nw.csv")
dmg <- read_csv("demo_lang_vsl_pca.csv")
```

Format Files

```
# Concatenate datasets
rt <- bind_rows(Hampshire = rt_1,
               Providence = rt_2,
               .id = "location")

rt_dmg <- right_join(dmg, rt, join_by(SubjID == subject_nr)) # Join Participant Demographic and Lang Data
rt_dmg <- rt_dmg |> mutate(target = tolower(target))
rt_dmg_cor <- rt_dmg |> filter(correct == 1)

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

# Define Factors and Conditions
rt_exp_cln <- 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_cln |> filter(trial_type == "CW") |> select(- complexity)
rt_nwords <- rt_exp_cln |> 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))

# Create a median-split factor for base frequency
rt_words_frq$BF_MedianSplit <- ifelse(
  rt_words_frq$Log10BF <= median(rt_words_frq$Log10BF, na.rm = TRUE),
  "Low", "High")
rt_words_frq$BF_MedianSplit <- factor(rt_words_frq$BF_MedianSplit, levels = c("Low", "High"))
rt_words_frq$FS_Split <- factor(rt_words_frq$FS_Split)

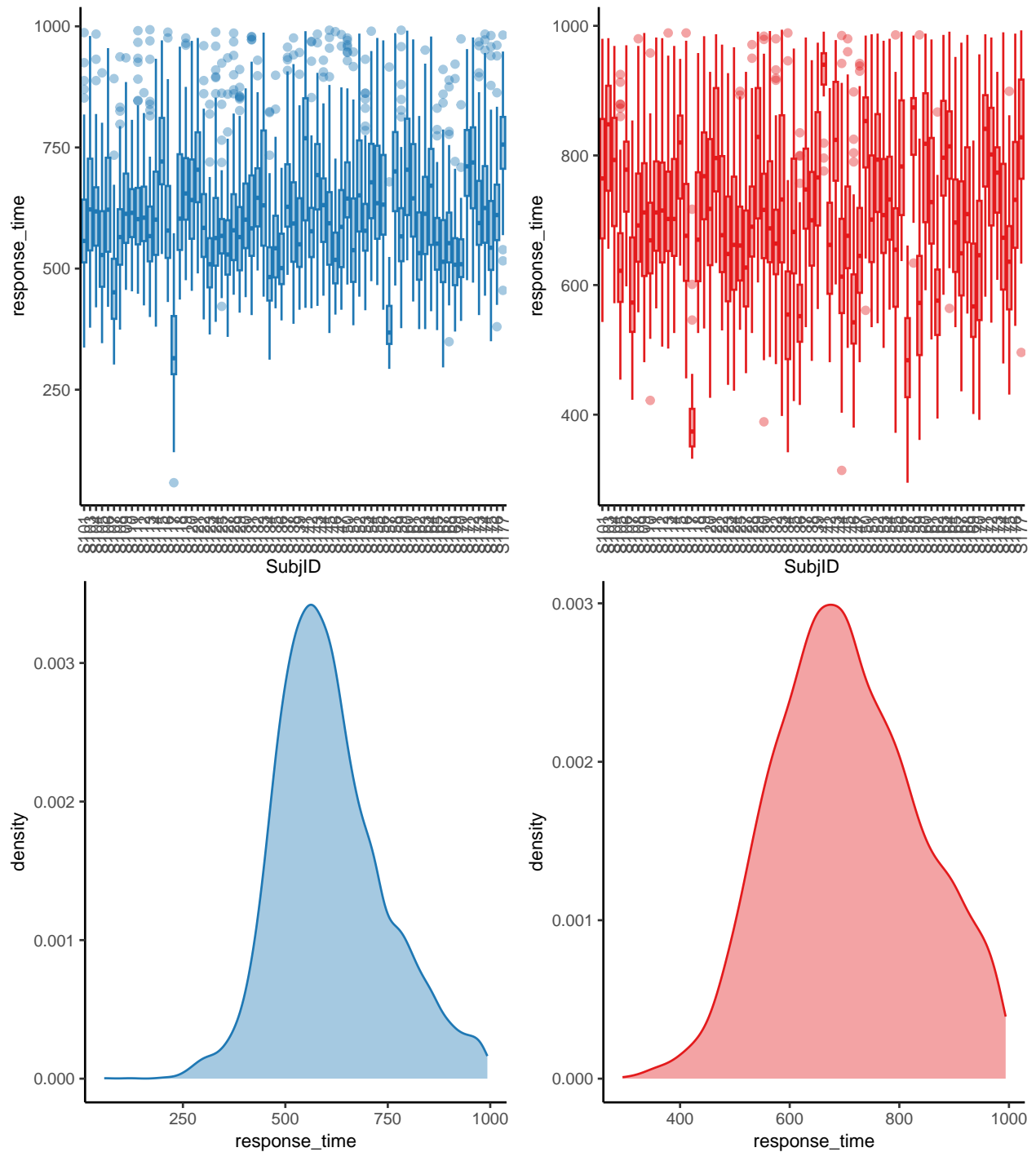
rt_nwords_frq$BF_Split <- factor(rt_nwords_frq$BF_Split)
rt_nwords_frq$FS_Split <- factor(rt_nwords_frq$FS_Split)
```

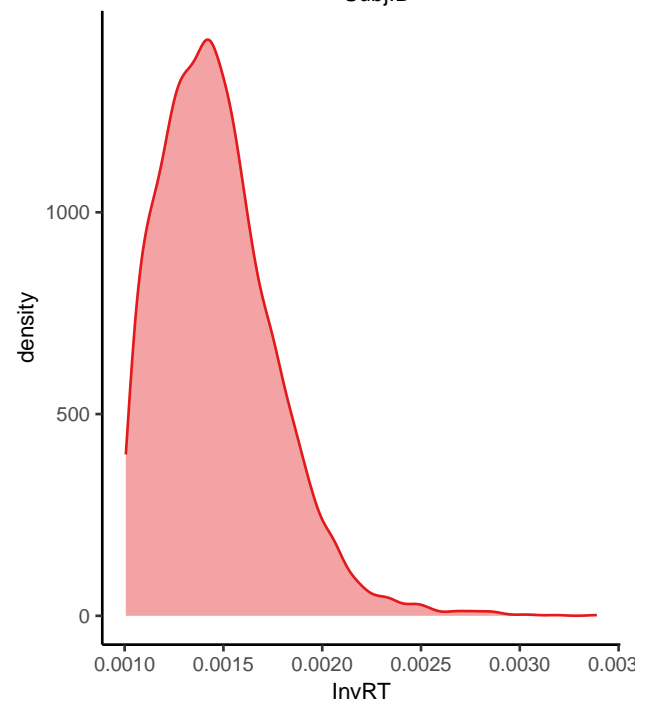
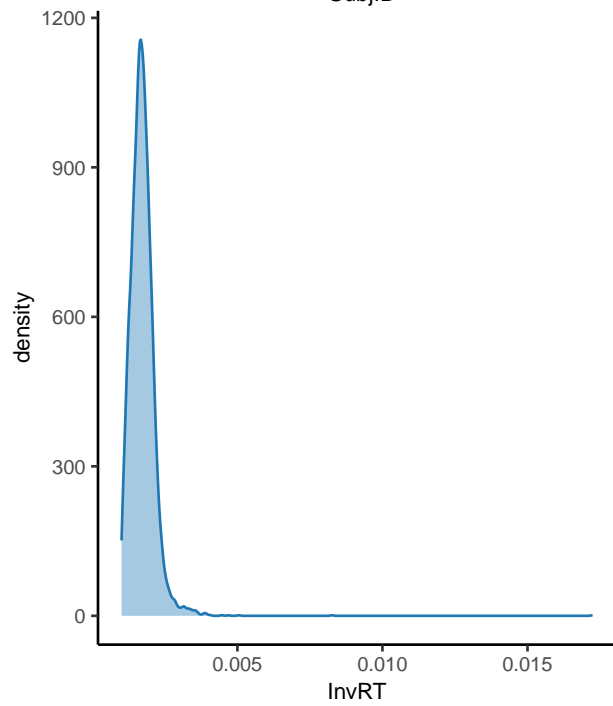
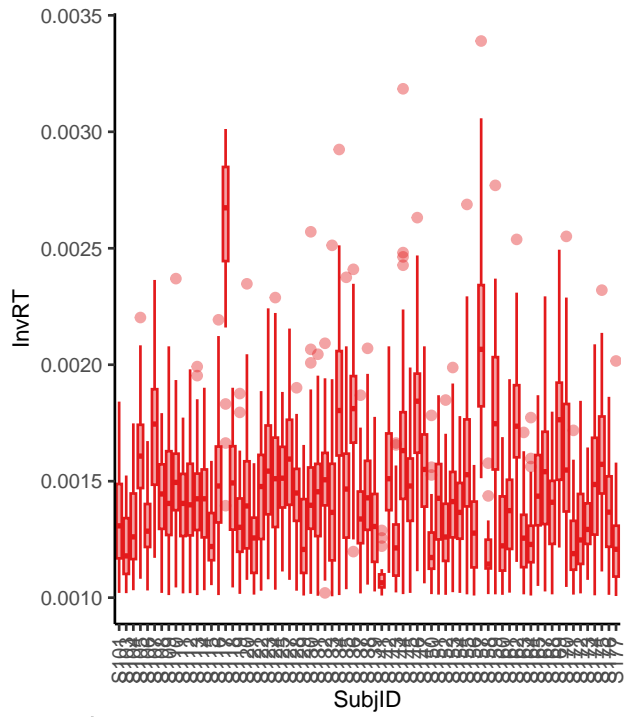
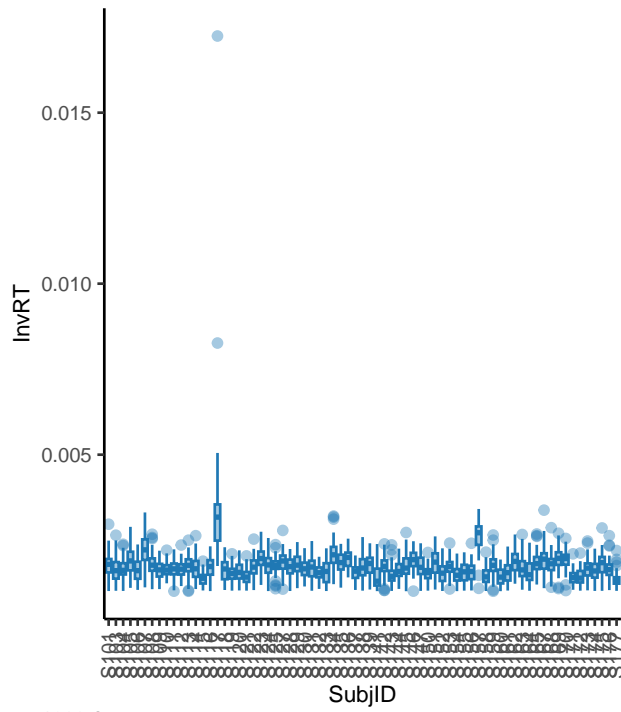
```
# Divide into cohorts
rt_words_1 <- rt_words_frq |> filter(location == "Hampshire") |> select(- location)
rt_words_2 <- rt_words_frq |> filter(location == "Providence") |> select(- location)

rt_nwords_1 <- rt_nwords_frq |> filter(location == "Hampshire") |> select(- location)
rt_nwords_2 <- rt_nwords_frq |> filter(location == "Providence") |> select(- location)
# str(rt_words_1)
```

Analyse Data

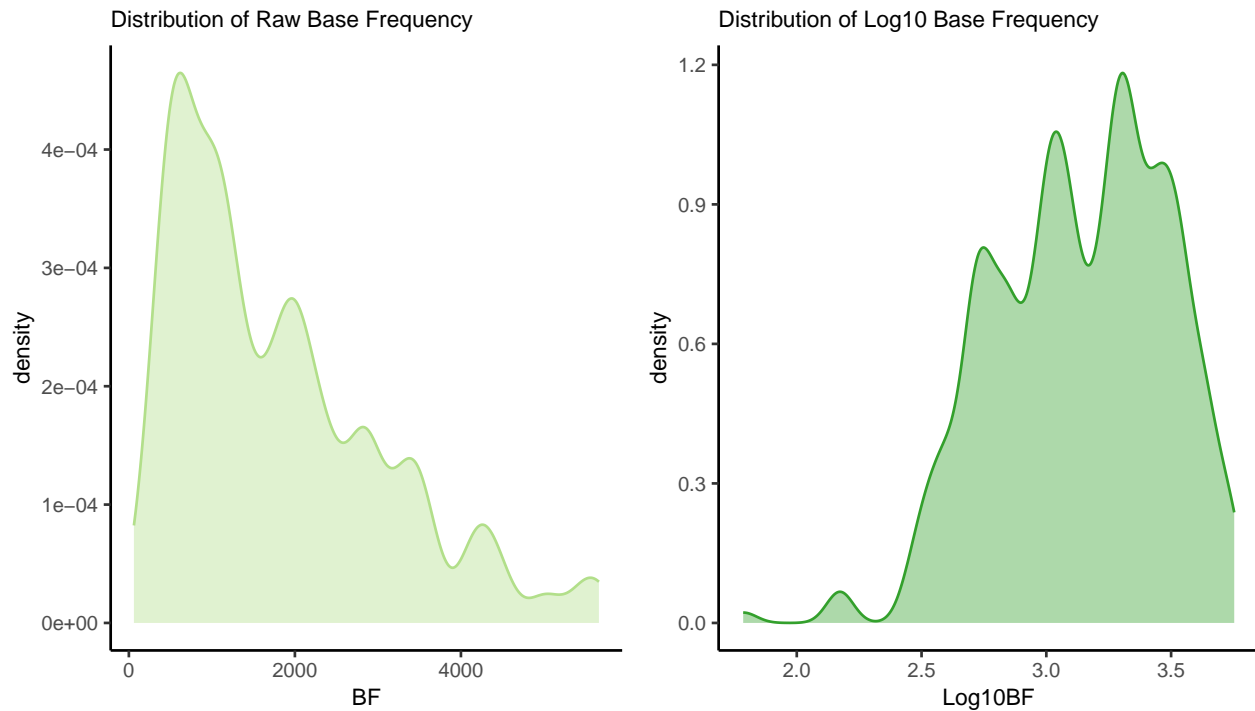
Plot RT distributions





Is Base Frequency Skewed

...



```
|| [1] 0.9870676
|| [1] -0.4166518
```

ANOVA Words

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

Standardize the predictors

```
rt_words_1_cmpl$Log10BF_std <- as.numeric(scale(rt_words_1_cmpl$Log10BF, center = TRUE, scale = TRUE))
rt_words_1_cmpl$FS_std <- as.numeric(scale(rt_words_1_cmpl$FS, center = TRUE, scale = TRUE))
rt_words_1_cmpl$Log10WF_std <- as.numeric(scale(rt_words_1_cmpl$Log10WF, center = TRUE, scale = TRUE))
rt_words_1_cmpl$Dim.2_std <- as.numeric(scale(rt_words_1_cmpl$Dim.2, center = TRUE, scale = TRUE))
```

Anova with Continuous Log10BF

```
anova_model_1 <- mixed(
  InvRT ~ Log10BF_std * FS_Split * lang_type_ortho + (1 | SubjID),
  data = rt_words_1_cmpl,
  method = "KR"
)
anova_model_1

|| Mixed Model Anova Table (Type 3 tests, KR-method)
||
|| Model: InvRT ~ Log10BF_std * FS_Split * lang_type_ortho + (1 | SubjID)
|| Data: rt_words_1_cmpl
||
||      Effect      df      F p.value
|| 1      Log10BF_std 1, 5792.69 41.88 *** <.001
|| 2      FS_Split 1, 5792.31 23.20 *** <.001
|| 3      lang_type_ortho 1, 64.02 2.40 .127
|| 4      Log10BF_std:FS_Split 1, 5792.52 0.03 .854
|| 5      Log10BF_std:lang_type_ortho 1, 5792.69 4.76 * .029
|| 6      FS_Split:lang_type_ortho 1, 5792.31 1.00 .318
|| 7      Log10BF_std:FS_Split:lang_type_ortho 1, 5792.52 0.24 .623
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(anova_model_1)
```

```
|| Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
|| Formula: InvRT ~ Log10BF_std * FS_Split * lang_type_ortho + (1 | SubjID)
|| Data: data
||
```

```

|| REML criterion at convergence: -75938.7
||
|| Scaled residuals:
||   Min       1Q   Median       3Q      Max
||  -4.265  -0.536  -0.017   0.527  38.870
||
|| Random effects:
||   Groups   Name                Variance Std.Dev.
||   SubjID   (Intercept)  7.771e-08  0.0002788
||   Residual                    1.293e-07  0.0003596
|| Number of obs: 5864, groups: SubjID, 66
||
|| Fixed effects:
||
||              Estimate Std. Error      df t value Pr(>|t|)
|| (Intercept)    1.734e-03  3.504e-05  6.390e+01  49.479 < 2e-16 ***
|| Log10BF_std    3.204e-05  4.950e-06  5.793e+03   6.472 1.05e-10 ***
|| FS_Split1     2.301e-05  4.777e-06  5.792e+03   4.816 1.50e-06 ***
|| lang_type_ortho1  5.423e-05  3.504e-05  6.390e+01   1.548  0.1266
|| Log10BF_std:FS_Split1  9.119e-07  4.948e-06  5.792e+03   0.184  0.8538
|| Log10BF_std:lang_type_ortho1  1.079e-05  4.950e-06  5.793e+03   2.181  0.0293 *
|| FS_Split1:lang_type_ortho1 -4.767e-06  4.777e-06  5.792e+03  -0.998  0.3183
|| Log10BF_std:FS_Split1:lang_type_ortho1  2.435e-06  4.948e-06  5.792e+03   0.492  0.6227
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
||
|| Correlation of Fixed Effects:
||      (Intr) Lg10BF_ FS_Sp1 lng__1 Lg10BF_:FS_S1 L10BF_:_ FS_S1:
|| Log10BF_std    -0.003
|| FS_Split1       0.001 -0.079
|| lng_typ_rt1     0.152  0.000  0.002
|| Lg10BF_:FS_S1  -0.011  0.249 -0.020 -0.002
|| Lg10BF_:__1    0.000  0.188 -0.013 -0.003  0.068
|| FS_Sp1:__1     0.002 -0.013  0.160  0.001 -0.004      -0.079
|| L10BF_:FS_S1:  -0.002  0.068 -0.004 -0.011  0.188      0.249   -0.020

```

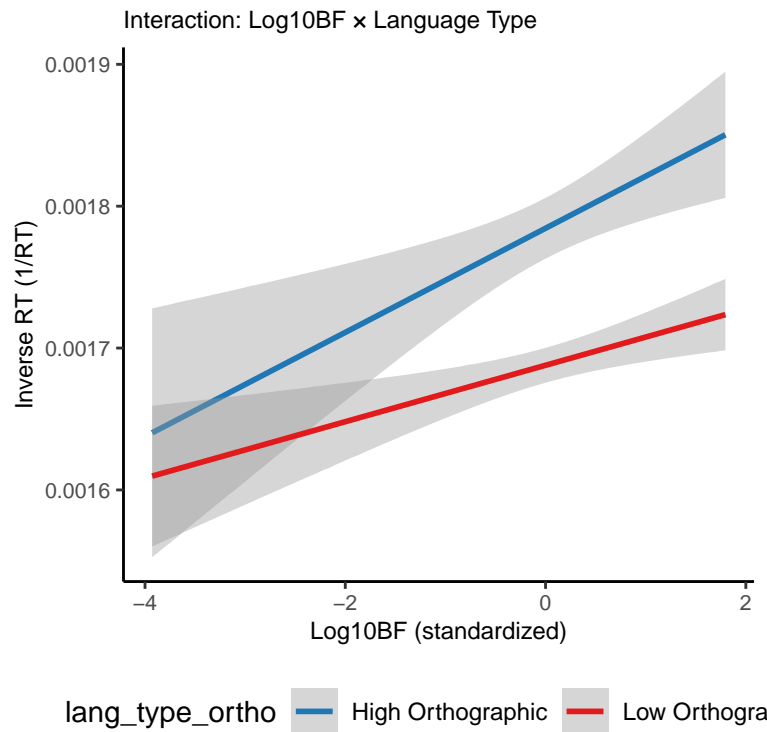
Main Findings:

Effect	df	F	p.value
Log10BF_std	1, 5792.69	41.88 ***	<.001
FS_Split	1, 5792.31	23.20 ***	<.001
Log10BF_std:lang_type_ortho	1, 5792.69	4.76 *	.029

Data show that as Log10BF increases (e.g., more frequent or predictable words), processing becomes faster (inverse RT goes up → RT goes down).

Statistical models were fit using inverse response time (1/RT) to capture processing speed, but all reported means and figures are back-transformed to milliseconds for interpretability.

Plots Plotting Processing Efficiency



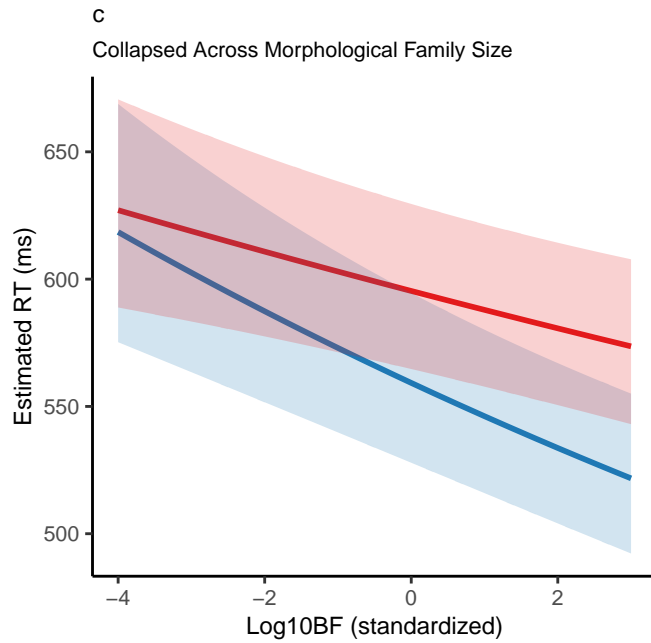
Plotting Latency To plot predicted values in milliseconds (RT) instead of inverse RT, you must:

1. Predict inverse RT values from the model
2. Back-transform to milliseconds with $RT_{ms} = 1000 / InvRT$
3. Plot the transformed values

When using `ggeffects` (or `emmeans`) with models fit using `afex::mixed()`. The `mixed()` function wraps `lmer()` from `lme4`, but the result isn't always fully compatible with tools like `ggeffects` because of the extra layers (especially when using Kenward-Roger or parametric bootstrap methods for inference).

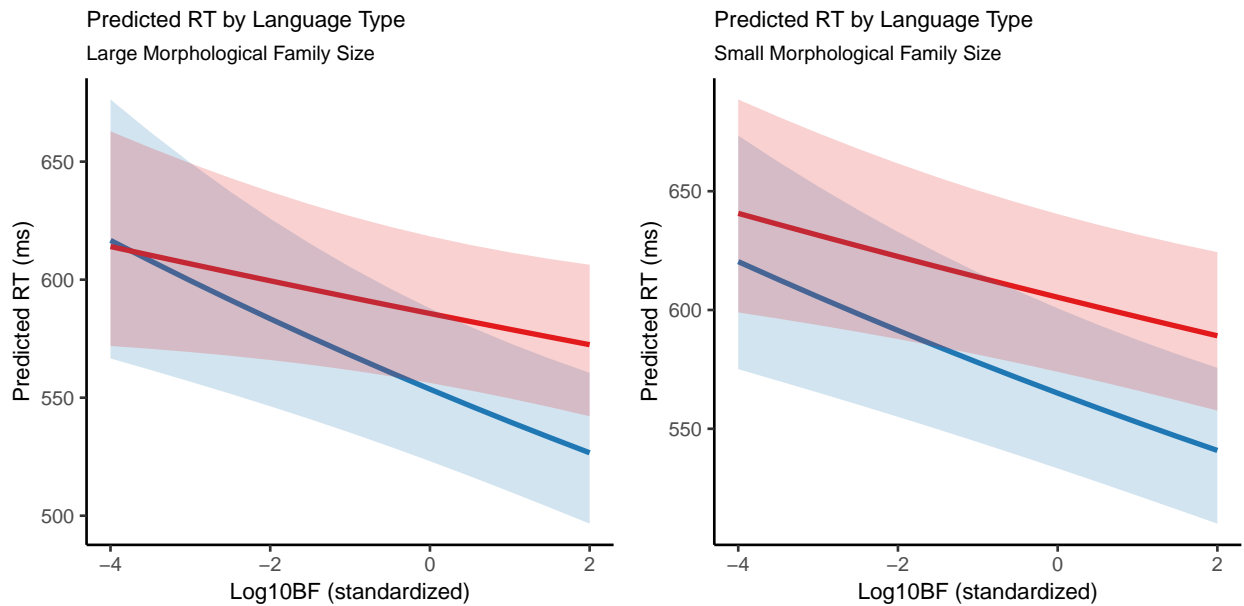
Because we are only using `mixed()` for the Kenward-Roger p-values but don't need it for prediction, refit our model with `lmer()`:

Option 1: Collapsed across Family Size ...



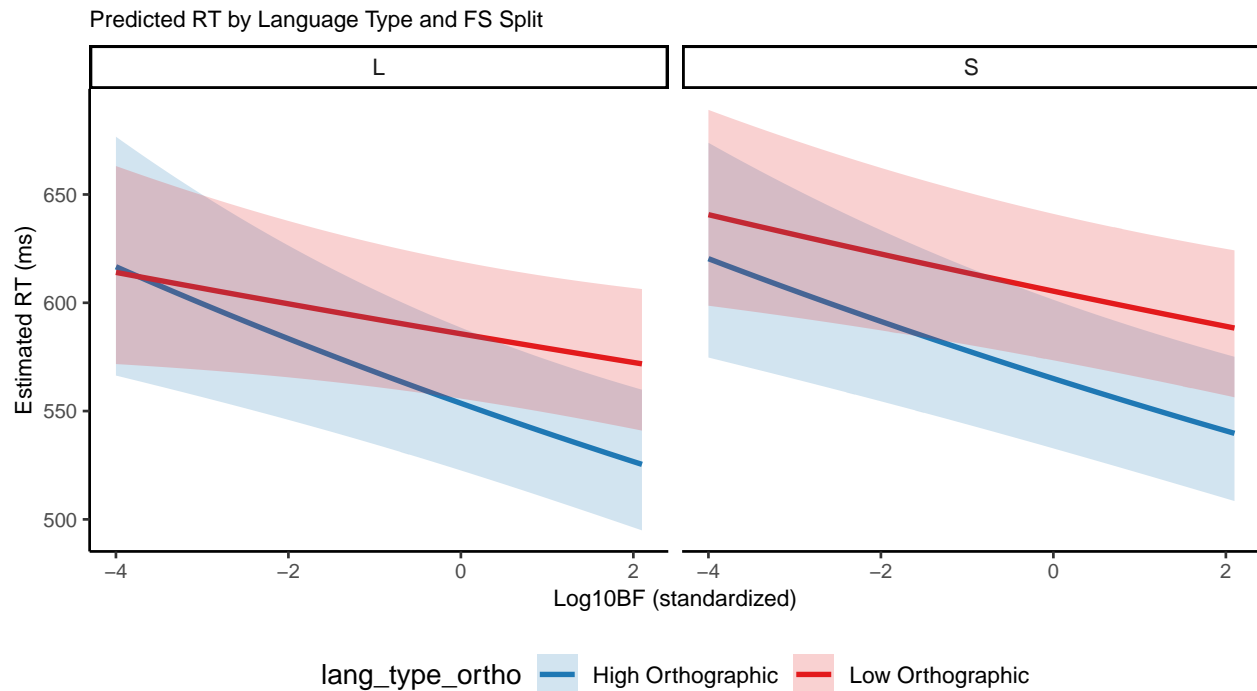
lang_type_ortho — High Orthographic — Low Orthographic

Option 2: LogBR x Language Type as a function of FS ...



Language Type — High Orthographic — Low Orthographic Language Type — High Orthographic — Low Orthographic

Option 3: LogBR x Language Type as a function of FS (Faceted Plot) ...



Interpret Interactions

```
# Marginal trends (i.e., slopes of Log10BF for each language group)
emtrends(anova_model_1, ~ lang_type_ortho, var = "Log10BF_std")
```

Contrast Slopes

```
|| lang_type_ortho Log10BF_std.trend SE df lower.CL upper.CL
|| High Orthographic 4.28e-05 7.63e-06 5793 2.79e-05 5.78e-05
|| Low Orthographic 2.12e-05 6.31e-06 5793 8.88e-06 3.36e-05
||
|| Results are averaged over the levels of: FS_Split
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95

# Formal contrast of slopes
emtrends(anova_model_1, pairwise ~ lang_type_ortho, var = "Log10BF_std")

|| $emtrends
|| lang_type_ortho Log10BF_std.trend SE df lower.CL upper.CL
|| High Orthographic 4.28e-05 7.63e-06 5793 2.79e-05 5.78e-05
|| Low Orthographic 2.12e-05 6.31e-06 5793 8.88e-06 3.36e-05
||
|| Results are averaged over the levels of: FS_Split
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95

|| $contrasts
|| contrast estimate SE df t.ratio p.value
|| High Orthographic - Low Orthographic 2.16e-05 9.9e-06 5793 2.181 0.0293
||
|| Results are averaged over the levels of: FS_Split
|| Degrees-of-freedom method: kenward-roger
```

```
library(emmeans)

# Estimate inverse RT at mean frequency for each group
emm <- emmeans(anova_model_lmer, ~ lang_type_ortho, at = list(Log10BF_std = 0))
emm_df <- as.data.frame(emm)

# Back-transform to ms
emm_df$RT_ms <- 1 / emm_df$emmean

print(emm_df)
```

Get ms estimates


```

|| lang_type_ortho      emmean      SE      df      lower.CL      upper.CL      RT_ms
|| High Orthographic 0.001788147 5.318219e-05 64.02 0.001681904 0.001894390 559.2381
|| Low Orthographic 0.001679678 4.564910e-05 64.01 0.001588483 0.001770872 595.3523
||
|| Results are averaged over the levels of: FS_Split
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95

```

Other ANOVA Models

Anova with Continuous Log10BF AND Continous FS

```

anova_model_2 <- mixed(
  InvRT ~ Log10BF_std * FS * lang_type_ortho + (1 | SubjID),
  data = rt_words_1_cmpl,
  method = "KR"
)
anova_model_2

```

```

|| Mixed Model Anova Table (Type 3 tests, KR-method)
||
|| Model: InvRT ~ Log10BF_std * FS * lang_type_ortho + (1 | SubjID)
|| Data: rt_words_1_cmpl
||
||      Effect      df      F p.value
|| 1      Log10BF_std 1, 5792.43 13.78 *** <.001
|| 2              FS 1, 5792.32  9.15 **  .003
|| 3      lang_type_ortho 1, 70.20  2.97 +  .089
|| 4      Log10BF_std:FS 1, 5792.35  0.02  .902
|| 5      Log10BF_std:lang_type_ortho 1, 5792.43  0.32  .570
|| 6              FS:lang_type_ortho 1, 5792.32  1.07  .300
|| 7      Log10BF_std:FS:lang_type_ortho 1, 5792.35  0.53  .469
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
summary(anova_model_2)
```

```

|| Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
|| Formula: InvRT ~ Log10BF_std * FS * lang_type_ortho + (1 | SubjID)
|| Data: data
||
|| REML criterion at convergence: -75909.6
||
|| Scaled residuals:
||      Min      1Q  Median      3Q      Max
|| -4.289 -0.536 -0.012  0.525 38.796
||
|| Random effects:
|| Groups Name      Variance Std.Dev.
|| SubjID (Intercept) 7.778e-08 0.0002789
|| Residual      1.296e-07 0.0003601
|| Number of obs: 5864, groups: SubjID, 66
||
|| Fixed effects:
||
||              Estimate Std. Error      df t value Pr(>|t|)
|| (Intercept)      1.711e-03  3.588e-05  7.008e+01  47.676 < 2e-16 ***
|| Log10BF_std      3.266e-05  8.798e-06  5.792e+03  3.712 0.000207 ***
|| FS              2.250e-06  7.440e-07  5.792e+03  3.024 0.002503 **
|| lang_type_ortho1  6.185e-05  3.588e-05  7.008e+01  1.724 0.089165 .
|| Log10BF_std:FS   -1.068e-07  8.677e-07  5.792e+03  -0.123 0.902013
|| Log10BF_std:lang_type_ortho1  5.003e-06  8.798e-06  5.792e+03  0.569 0.569624
|| FS:lang_type_ortho1 -7.705e-07  7.440e-07  5.792e+03  -1.036 0.300396
|| Log10BF_std:FS:lang_type_ortho1  6.288e-07  8.677e-07  5.792e+03  0.725 0.468733
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

|| Correlation of Fixed Effects:
||      (Intr) Lg10BF_ FS      lng__1 Lg10BF_:FS L10BF:_ FS:__1
|| Log10BF_std -0.010
|| FS          -0.212 0.122
|| lng_typ_rt1 0.152 -0.002 -0.033
|| Lg10BF_s:FS 0.029 -0.837 -0.223 0.005
|| Lg10BF:___1 -0.002 0.170 0.019 -0.010 -0.142
|| FS:lng_ty_1 -0.033 0.019 0.161 -0.212 -0.036 0.122
|| L10BF_:FS:_ 0.005 -0.142 -0.036 0.029 0.174 -0.837 -0.223

```

Anova with Categorical Log10BF and Categorical Log10BF

```

anova_model_2 <- mixed(
  InvRT ~ BF_MedianSplit * FS_Split * lang_type_ortho + (1 | SubjID),
  data = rt_words_1_cmpl,
  method = "KR"
)
anova_model_2

```

```

|| Mixed Model Anova Table (Type 3 tests, KR-method)
||
|| Model: InvRT ~ BF_MedianSplit * FS_Split * lang_type_ortho + (1 | SubjID)
|| Data: rt_words_1_cmpl
||
||      Effect      df      F p.value
|| 1 BF_MedianSplit 1, 5792.35 34.10 *** <.001
|| 2 FS_Split 1, 5792.32 27.80 *** <.001
|| 3 lang_type_ortho 1, 64.00 2.43 .124
|| 4 BF_MedianSplit:FS_Split 1, 5792.32 4.69 * .030
|| 5 BF_MedianSplit:lang_type_ortho 1, 5792.35 1.38 .239
|| 6 FS_Split:lang_type_ortho 1, 5792.32 0.70 .404
|| 7 BF_MedianSplit:FS_Split:lang_type_ortho 1, 5792.32 0.33 .566
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
summary(anova_model_2)

|| Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
|| Formula: InvRT ~ BF_MedianSplit * FS_Split * lang_type_ortho + (1 | SubjID)
|| Data: data
||
|| REML criterion at convergence: -75932.5
||
|| Scaled residuals:
||      Min       1Q   Median       3Q      Max
|| -4.245 -0.535 -0.007  0.526 38.831
||
|| Random effects:
|| Groups   Name      Variance Std.Dev.
|| SubjID    (Intercept) 7.741e-08 0.0002782
|| Residual              1.295e-07 0.0003598
|| Number of obs: 5864, groups: SubjID, 66
||
|| Fixed effects:
||
||              Estimate Std. Error      df t value Pr(>|t|)
|| (Intercept)      1.734e-03  3.498e-05  6.389e+01  49.586 < 2e-16 ***
|| BF_MedianSplit1 -2.782e-05  4.765e-06  5.792e+03  -5.839 5.52e-09 ***
|| FS_Split1        2.512e-05  4.765e-06  5.792e+03   5.272 1.40e-07 ***
|| lang_type_ortho1  5.450e-05  3.498e-05  6.389e+01   1.558  0.1241
|| BF_MedianSplit1:FS_Split1 1.031e-05  4.765e-06  5.792e+03   2.165  0.0305 *
|| BF_MedianSplit1:lang_type_ortho1 -5.607e-06  4.765e-06  5.792e+03  -1.177  0.2393
|| FS_Split1:lang_type_ortho1 -3.976e-06  4.765e-06  5.792e+03  -0.835  0.4040
|| BF_MedianSplit1:FS_Split1:lang_type_ortho1 2.738e-06  4.765e-06  5.792e+03   0.575  0.5656
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
||
|| Correlation of Fixed Effects:
||
||      (Intr) BF_MdS1 FS_Sp1 lng__1 BF_MdS1:FS_S1 BF_MS1:_ FS_S1:
|| BF_MdnSpl1t1 -0.001
|| FS_Split1    0.001 0.007
|| lng_typ_rt1  0.152 -0.001 0.002
|| BF_MdS1:FS_S1 0.001 0.006 -0.011 -0.001
|| BF_MdS1:__1 -0.001 0.161 -0.003 -0.001 0.011
|| FS_Sp1:__1  0.002 -0.003 0.161 0.001 -0.005 0.007
|| BF_MS1:FS_S1: -0.001 0.011 -0.005 0.001 0.161 0.006 -0.011

```

ANOVA Non-Words

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

Standardize the predictors

```

rt_nwords_1_cmpl$LogBF_std <- as.numeric(scale(rt_nwords_1_cmpl$LogBF, center = TRUE, scale = TRUE))
rt_nwords_1_cmpl$FS_std <- as.numeric(scale(rt_nwords_1_cmpl$FS, center = TRUE, scale = TRUE))
rt_nwords_1_cmpl$BF_std <- as.numeric(scale(rt_nwords_1_cmpl$BF, center = TRUE, scale = TRUE))
rt_nwords_1_cmpl$Dim.2_std <- as.numeric(scale(rt_nwords_1_cmpl$Dim.2, center = TRUE, scale = TRUE))

```

Anova with Continuous Log10BF

```

anova_model_2 <- mixed(
  InvRT ~ LogBF_std * FS_Split * lang_type_ortho + (1 | SubjID),
  data = rt_nwords_1_cmpl,
  method = "KR"
)
anova_model_2

|| Mixed Model Anova Table (Type 3 tests, KR-method)
||
|| Model: InvRT ~ LogBF_std * FS_Split * lang_type_ortho + (1 | SubjID)

```

```

|| Data: rt_nwords_1_cmpl
||
||      Effect      df      F p.value
|| 1      LogBF_std 1, 4599.88 18.20 *** <.001
|| 2      FS_Split 1, 4599.59      0.45   .503
|| 3      lang_type_ortho 1, 64.77      2.08   .154
|| 4      LogBF_std:FS_Split 1, 4599.56 2.71 +   .100
|| 5      LogBF_std:lang_type_ortho 1, 4599.88      0.00   .963
|| 6      FS_Split:lang_type_ortho 1, 4599.59      1.95   .163
|| 7 LogBF_std:FS_Split:lang_type_ortho 1, 4599.56      0.08   .771
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
summary(anova_model_2)

|| Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
|| Formula: InvRT ~ LogBF_std * FS_Split * lang_type_ortho + (1 | SubjID)
|| Data: data
||
|| REML criterion at convergence: -64447.7
||
|| Scaled residuals:
||      Min       1Q   Median       3Q      Max
|| -4.5501 -0.6812 -0.0551  0.6288  6.5563
||
|| Random effects:
|| Groups      Name                Variance Std.Dev.
|| SubjID      (Intercept) 4.687e-08 0.0002165
|| Residual                    5.428e-08 0.0002330
|| Number of obs: 4671, groups: SubjID, 66
||
|| Fixed effects:
||
||              Estimate Std. Error      df t value Pr(>|t|)
|| (Intercept)      1.466e-03  2.729e-05 6.309e+01  53.731 < 2e-16 ***
|| LogBF_std      -1.747e-05  4.096e-06 4.598e+03  -4.266 2.03e-05 ***
|| FS_Split1       2.730e-06  4.072e-06 4.598e+03   0.670  0.5026
|| lang_type_ortho1 3.940e-05  2.729e-05 6.309e+01   1.443  0.1538
|| LogBF_std:FS_Split1 6.736e-06  4.093e-06 4.598e+03   1.646  0.0999
|| LogBF_std:lang_type_ortho1 -1.894e-07  4.096e-06 4.598e+03  -0.046  0.9631
|| FS_Split1:lang_type_ortho1 5.684e-06  4.072e-06 4.598e+03   1.396  0.1629
|| LogBF_std:FS_Split1:lang_type_ortho1 1.192e-06  4.093e-06 4.598e+03   0.291  0.7709
|| ---
|| Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
||
|| Correlation of Fixed Effects:
||      (Intr) LgBF_s FS_Sp1 lng__1 LgBF_:FS_S1 LBF_:_ FS_S1:
|| LogBF_std    -0.013
|| FS_Split1     0.011 -0.535
|| lng_typ_rt1  0.150 -0.001 -0.001
|| LgBF_:FS_S1 -0.080  0.136 -0.087 -0.010
|| LgBF_st:_1 -0.001 -0.001  0.115 -0.065 -0.013 -0.009
|| FS_Spl1:_1 -0.001 -0.065  0.119  0.011  0.001   -0.535
|| LBF_:FS_S1: -0.010 -0.009  0.001 -0.080  0.114    0.136 -0.087

```

Main Findings:

Effect	df	F	p.value
Log10BF_std	1, 4599.88	18.20 ***	<.001

Data show that as Log10BF increases (e.g., more frequent or predictable words), processing becomes faster (inverse RT goes up → RT goes down).

Statistical models were fit using inverse response time (1/RT) to capture processing speed, but all reported means and figures are back-transformed to milliseconds for interpretability.

Follow up analyses

```
emtrends(anova_model_2, ~1, var = "LogBF_std")
```

Report Estimated Trend (Slope) for LogBF

```

|| 1      LogBF_std.trend      SE      df lower.CL upper.CL
|| overall      -1.75e-05 4.1e-06 4600 -2.55e-05 -9.44e-06
||
|| Results are averaged over the levels of: FS_Split, lang_type_ortho
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95

```

```
# estimate the slope of LogBF at each level of FS_Split:
emtrends(anova_model_2, ~ FS_Split, var = "LogBF_std")
```

Probe the Marginal LogBF × FS_Split Interaction

```
|| FS_Split LogBF_std.trend      SE   df  lower.CL  upper.CL
|| L          -1.07e-05 6.17e-06 4600 -2.28e-05  1.37e-06
|| S          -2.42e-05 5.38e-06 4600 -3.48e-05 -1.37e-05
||
|| Results are averaged over the levels of: lang_type_ortho
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95

# compare the two trends:
emtrends(anova_model_2, pairwise ~ FS_Split, var = "LogBF_std")

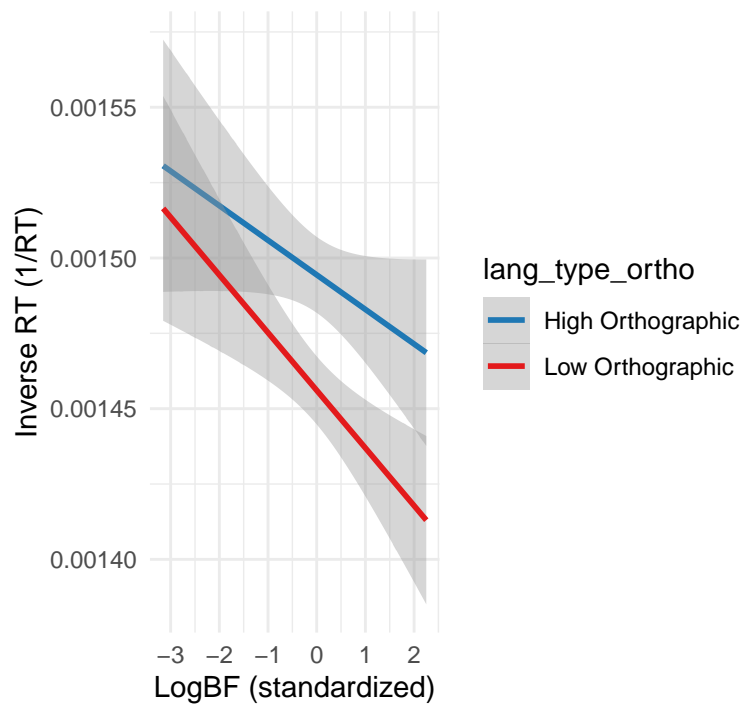
|| $emtrends
|| FS_Split LogBF_std.trend      SE   df  lower.CL  upper.CL
|| L          -1.07e-05 6.17e-06 4600 -2.28e-05  1.37e-06
|| S          -2.42e-05 5.38e-06 4600 -3.48e-05 -1.37e-05
||
|| Results are averaged over the levels of: lang_type_ortho
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
||
|| $contrasts
|| contrast estimate      SE   df t.ratio p.value
|| L - S      1.35e-05 8.19e-06 4600  1.646  0.0999
||
|| Results are averaged over the levels of: lang_type_ortho
|| Degrees-of-freedom method: kenward-roger
# Estimate marginal means of inverse RT at LogBF_std = 0
emm <- emmeans(anova_model_2, ~ FS_Split, at = list(LogBF_std = 0))
emm_df <- as.data.frame(emm)

# Back-transform to milliseconds
emm_df$RT_ms <- 1 / emm_df$emmean
emm_df$CI_low_ms <- 1 / emm_df$upper.CL # Note: upper bound of InvRT → lower RT
emm_df$CI_high_ms <- 1 / emm_df$lower.CL # lower bound of InvRT → upper RT
print(emm_df)

|| FS_Split      emmean      SE   df  lower.CL  upper.CL  RT_ms CI_low_ms CI_high_ms
|| L      0.001469183 2.763687e-05 68.10 0.001414036 0.001524330 680.6503  656.0258  707.1956
|| S      0.001463722 2.755216e-05 67.27 0.001408732 0.001518713 683.1896  658.4523  709.8581
||
|| Results are averaged over the levels of: lang_type_ortho
|| Degrees-of-freedom method: kenward-roger
|| Confidence level used: 0.95
```

Plots Plotting Processing Efficiency

Interaction: LogBF × Language Type

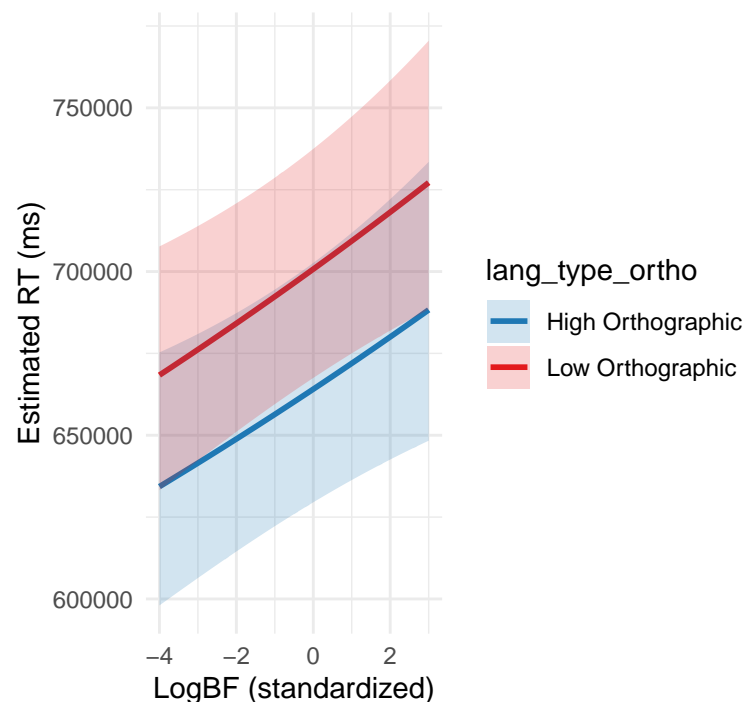


Plotting Latency To plot predicted values in milliseconds (RT) instead of inverse RT, you must: 1. Predict inverse RT values from the model 2. Back-transform to milliseconds with $RT_ms = 1000 / InvRT$ 3. Plot the transformed values

When using `ggeffects` (or `emmeans`) with models fit using `afex::mixed()`. The `mixed()` function wraps `lmer()` from `lme4`, but the result isn't always fully compatible with tools like `ggeffects` because of the extra layers (especially when using Kenward-Roger or parametric bootstrap methods for inference).

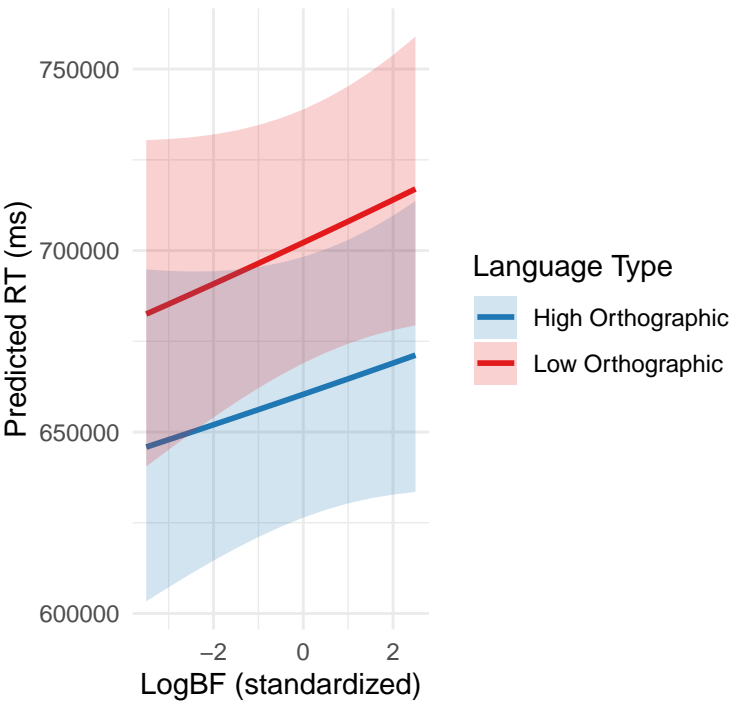
Because we are only using `mixed()` for the Kenward-Roger p-values but don't need it for prediction, refit our model with `lmer()`:

Predicted RT by Language Type



Option 1: Collapsed across Family Size

Effect of LogBF × Language Type on R



Option 2: LogBR x Language Type as a function of FS
Effect of LogBF × Language Type on RT:

