MP MetaAnalysis

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Contents


```
## Loading tidyverse: ggplot2
## Loading tidyverse: tibble
## Loading tidyverse: tidyr
## Loading tidyverse: readr
## Loading tidyverse: purrr
## Loading tidyverse: dplyr

## Conflicts with tidy packages ----------------------------------------------

## filter(): dplyr, stats
## lag():    dplyr, stats

## Loading required package: Matrix

##
## Attaching package: 'Matrix'
```

```
## The following object is masked from 'package:tidyr':
##
##     expand

## Loading 'metafor' package (version 1.9-9). For an overview
## and introduction to the package please type: help(metafor).

## Loading 'meta' package (version 4.9-0).
## Type 'help(meta)' for a brief overview.

##
## Attaching package: 'meta'

## The following objects are masked from 'package:metafor':
##
##     baujat, forest, funnel, funnel.default, labbe, radial,
##     trimfill
```

Preparation

Read in data and tidy up dataset

Plotting defaults

```r
# Themes and plot
apatheme = theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank(),
    panel.border = element_blank(), axis.line = element_line(), text = element_text(family = "Times",
        size = 25))
```

Descriptive data

The database contains data from 32 papers. In the tables below, we provide more descriptive information.

The next table shows what type of publications were included in our meta-analysis

publication_status	n_unique	count
dissertation	2	17
gray paper	2	14
paper	27	216
proceedings	1	4

Type of data on which we calculated effect sizes

The table below shows based on which data we calculated effect sizes.

es_method	n_unique	count
group_means_one	18	120
group_means_two	7	57
t_one	4	39

es_method	n_unique	count
t_two	5	35

Number of unique infants

The database contains data from 2252 unique infants.

Number of unique experimental conditions

The database contains data from 249 unique experimental conditions

Type of comparison of the time-course data calculated

We also have different ways of comparison of the time-course data, as the next table shows.

within_measure_descriptive	n_unique	count
post-naming compared to pre-naming phase	10	29
post-naming phase compared with chance (=50%)	9	23
post-pre difference score compared with chance (=0)	13	52

Type of distractor

This is a summary of the type of distractor used in an experiment

object_pair	count
familiar_familiar	23
familiar_novel	10

Whether word was pronounced both correctly as well as mispronounced

This is a summary of whether an experiment had both correct and mispronounced versions of the word in the experiment

word_correct_and_MP	count
	2
no	10
yes	21

Size of analysis time window

Where possible, we noted the time window for analysis. First, let's look at the offset (in milliseconds) after the start of the word, i.e. the begin of a give analysis window for a naming effect

```
offset_info <- time_wind_dat %>% group_by(offset) %>% summarize(count = n())
```

```r
kable(offset_info)
```

offset	count
0	3
200	1
231	1
267	1
300	1
360	5
365	1
367	14
400	1
500	1
1133	1
NA	4

Duration of post naming window

Next we look at duration (in seconds) of the post naming window, here,too, we see a lot of heterogeneity.

```r
duration_info <- db_ET_correct %>% group_by(post_nam_dur) %>% summarize(count = n())


kable(duration_info)
```

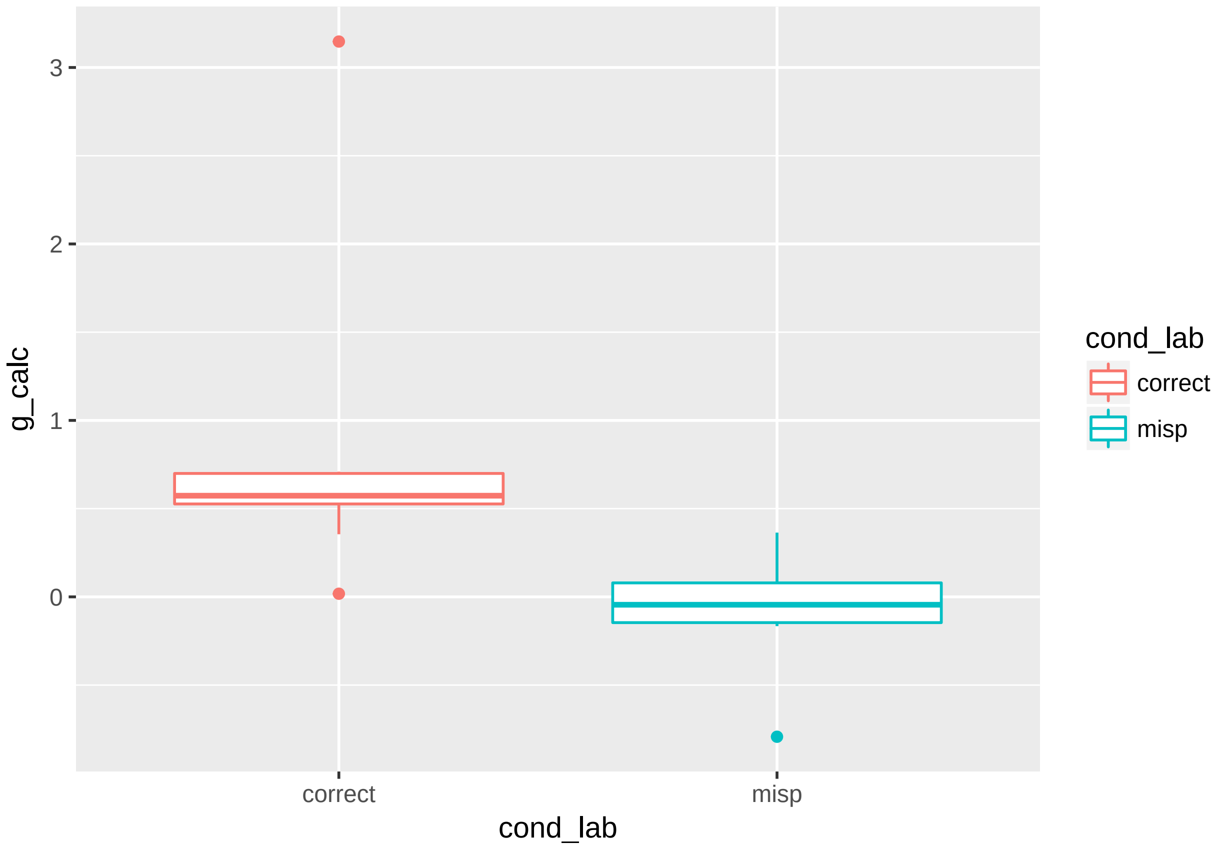
post_nam_dur	count
1.510	2
2.000	45
2.500	18
2.600	4
2.750	4
2.767	1
2.805	4
3.000	13
3.500	6
4.000	6
6.000	1

In summary, we see little consistency in analysis methods of comparable studies looking at naming and mispronunciation effects.

Mispronunciation Sensitivity in the youngest ages

Even the youngest ages in the database (less than 1 year) show mispronunciation sensitivity

```
## [1] Zesiger et al. (2012)       Mani & Plunkett 2010
## [3] Bergelson & Swingley (2017)
## 34 Levels: Altvater-Mackensen (2010) ... Zesiger et al. (2012)
```



Meta-Analysis

Main Mispronunciation Sensitivity Effects

Correct object identification effect

```
rma_correct = rma.mv(g_calc, g_var_calc, data = db_ET_correct, random = ~collapse |
    short_cite)

summary(rma_correct)
```

```
##
## Multivariate Meta-Analysis Model (k = 104; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -111.8857   223.7713   229.7713   237.6755   230.0137
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.4483  0.6696     no
```

```
## rho        0.8886             no
##
## Test for Heterogeneity:
## Q(df = 103) = 625.6267, p-val < .0001
##
## Model Results:
##
## estimate       se     zval     pval    ci.lb    ci.ub
##   0.9078   0.1198   7.5784   <.0001   0.6730   1.1426      ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# kable(round(coef(summary(rma_correct)), 2))
```

Mispronunciation object identification effect

```r
rma_MP = rma.mv(g_calc, g_var_calc, data = db_ET_MP, random = ~collapse | short_cite)

summary(rma_MP)
```

```
##
## Multivariate Meta-Analysis Model (k = 147; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -70.1217  140.2434  146.2434  155.1942  146.4124
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1192  0.3453     no
## rho        0.5924             no
##
## Test for Heterogeneity:
## Q(df = 146) = 462.5143, p-val < .0001
##
## Model Results:
##
## estimate       se     zval     pval    ci.lb    ci.ub
##   0.2498   0.0597   4.1835   <.0001   0.1328   0.3668      ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Mispronunciation Sensitivity effect

```r
db_ET_correct$condition <- 1
db_ET_MP$condition <- 0
```

```r
dat <- bind_rows(db_ET_correct, db_ET_MP)

rma_MPeffect <- rma.mv(g_calc, g_var_calc, mods = ~condition, data = dat, random = ~collapse |
    short_cite)

summary(rma_MPeffect)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -252.9095   505.8189   513.8189   527.8887   513.9829
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1371  0.3703     no
## rho        0.7381             no
##
## Test for Residual Heterogeneity:
## QE(df = 249) = 1088.1411, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 215.7609, p-val < .0001
##
## Model Results:
##
##            estimate      se     zval    pval   ci.lb   ci.ub
## intrcpt      0.2792  0.0652   4.2827  <.0001  0.1514  0.4069  ***
## condition    0.4953  0.0337  14.6888  <.0001  0.4293  0.5614  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
rma_MPeffect_1 <- rma.mv(g_calc, g_var_calc, mods = ~condition - 1, data = dat,
    random = ~collapse | short_cite)

summary(rma_MPeffect_1)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -261.1359   522.2718   528.2718   538.8362   528.3694
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
```

```
## tau^2      0.2069  0.4549     no
## rho        0.8295             no
##
## Test for Residual Heterogeneity:
## QE(df = 250) = 1154.4618, p-val < .0001
##
## Model Results:
##
##            estimate      se     zval    pval   ci.lb   ci.ub
## condition    0.5139  0.0333  15.4186  <.0001  0.4486  0.5793  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Main Mispronunciation Sensitivity Effects with Age Moderators

Correct object identification effect with age moderator

```
rma_correct_age = rma.mv(g_calc, g_var_calc, mods = ~age.C, data = db_ET_correct,
    random = ~collapse | short_cite)

summary(rma_correct_age)
```

```
##
## Multivariate Meta-Analysis Model (k = 104; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -110.8134   221.6268   229.6268   240.1267   230.0392
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.4458  0.6677     no
## rho        0.8835             no
##
## Test for Residual Heterogeneity:
## QE(df = 102) = 619.1502, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.6778, p-val = 0.4103
##
## Model Results:
##
##          estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt    0.9202  0.1203  7.6515  <.0001   0.6845  1.1559  ***
## age.C      0.0145  0.0176  0.8233  0.4103  -0.0200  0.0490
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# kable(round(coef(summary(rma_correct_age)), 2))
```

Mispronunciation object identification effect with age moderator

```r
rma_MP_age = rma.mv(g_calc, g_var_calc, mods = ~age.C, data = db_ET_MP, random = ~collapse |
    short_cite)

summary(rma_MP_age)
```

```
##
## Multivariate Meta-Analysis Model (k = 147; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -68.8541  137.7083  145.7083  157.6152  145.9940
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1181  0.3437     no
## rho        0.5830             no
##
## Test for Residual Heterogeneity:
## QE(df = 145) = 449.1871, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 1.7151, p-val = 0.1903
##
## Model Results:
##
##          estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt    0.2613  0.0599  4.3583  <.0001   0.1438  0.3788  ***
## age.C      0.0149  0.0114  1.3096  0.1903  -0.0074  0.0372
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Mispronunciation Sensitivity effect with age moderator

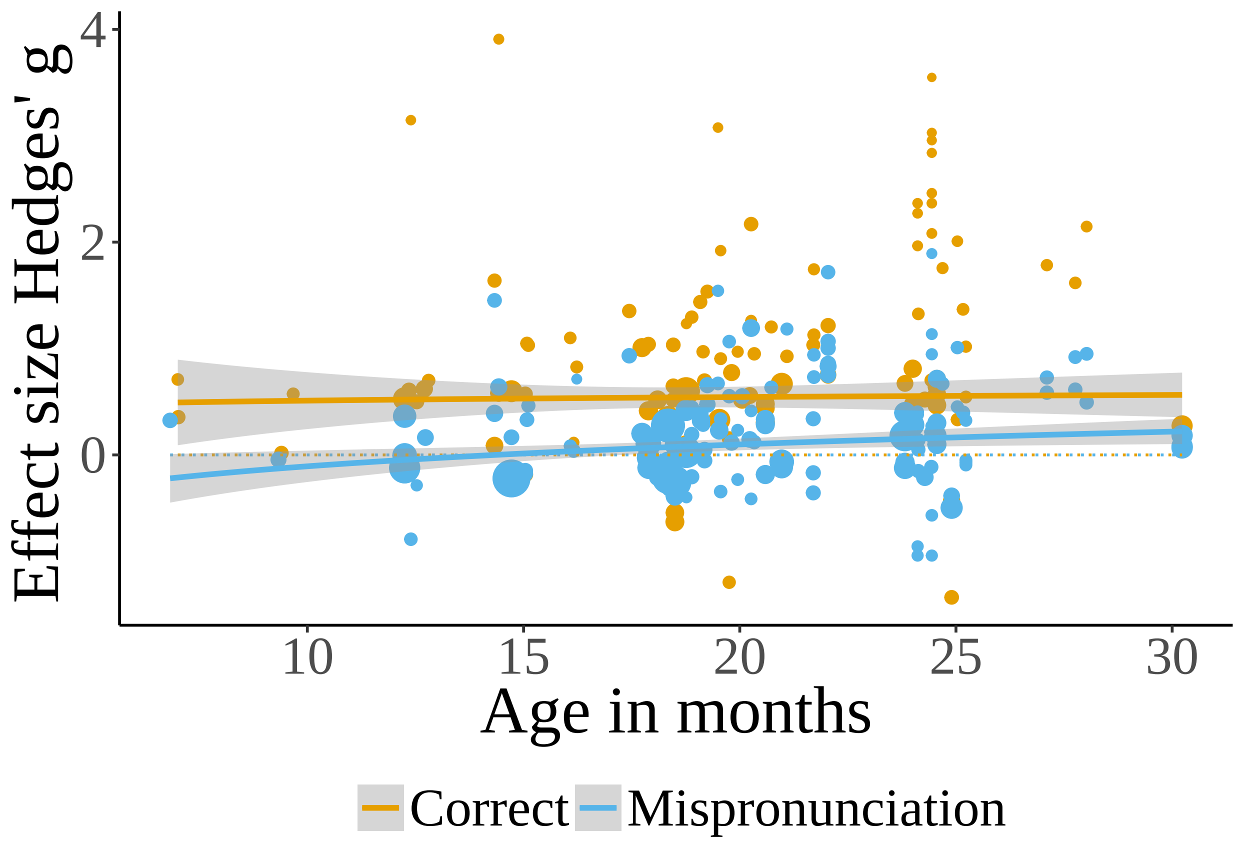
```r
db_ET_correct$condition <- 1
db_ET_MP$condition <- 0

dat <- bind_rows(db_ET_correct, db_ET_MP)

rma_MPeffect_age <- rma.mv(g_calc, g_var_calc, mods = ~age.C * condition, data = dat,
    random = ~collapse | short_cite)

summary(rma_MPeffect_age)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -251.2299   502.4597   514.4597   535.5160   514.8097
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1331  0.3648     no
## rho        0.7254             no
##
## Test for Residual Heterogeneity:
## QE(df = 247) = 1068.3373, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 218.6210, p-val < .0001
##
## Model Results:
##
##                  estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt            0.2935  0.0648   4.5324  <.0001   0.1666  0.4204  ***
## age.C              0.0171  0.0113   1.5136  0.1301  -0.0051  0.0393
## condition          0.4984  0.0344  14.4930  <.0001   0.4310  0.5658  ***
## age.C:condition    0.0026  0.0076   0.3436  0.7312  -0.0123  0.0175
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting Mispronunciation Effect

Plot Mispronunciation Effect by Age (color)

```r
dat$condition_label = ifelse(dat$condition == 1, "Correct", "Mispronunciation")

# Color Blind palette:
cbPalette <- c("#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "#D55E00",
    "#CC79A7")

p <- ggplot(dat, aes(mean_age_1/30.44, g_calc, color = condition_label)) + geom_point(aes(size = weights
    show.legend = FALSE) + geom_line(y = 0, linetype = "dotted") + geom_smooth(method = "lm",
    formula = y ~ log(x), aes(weight = weights_g)) + scale_colour_manual(values = cbPalette) +
    apatheme + theme(legend.title = element_blank(), legend.position = "bottom") +
    xlab("Age in months") + ylab("Effect size Hedges' g")

p
```




```
min(dat$mean_age_1/30.44)
```

```
## [1] 6.826544
```

```
max(dat$mean_age_1/30.44)
```

```
## [1] 30.22996
```

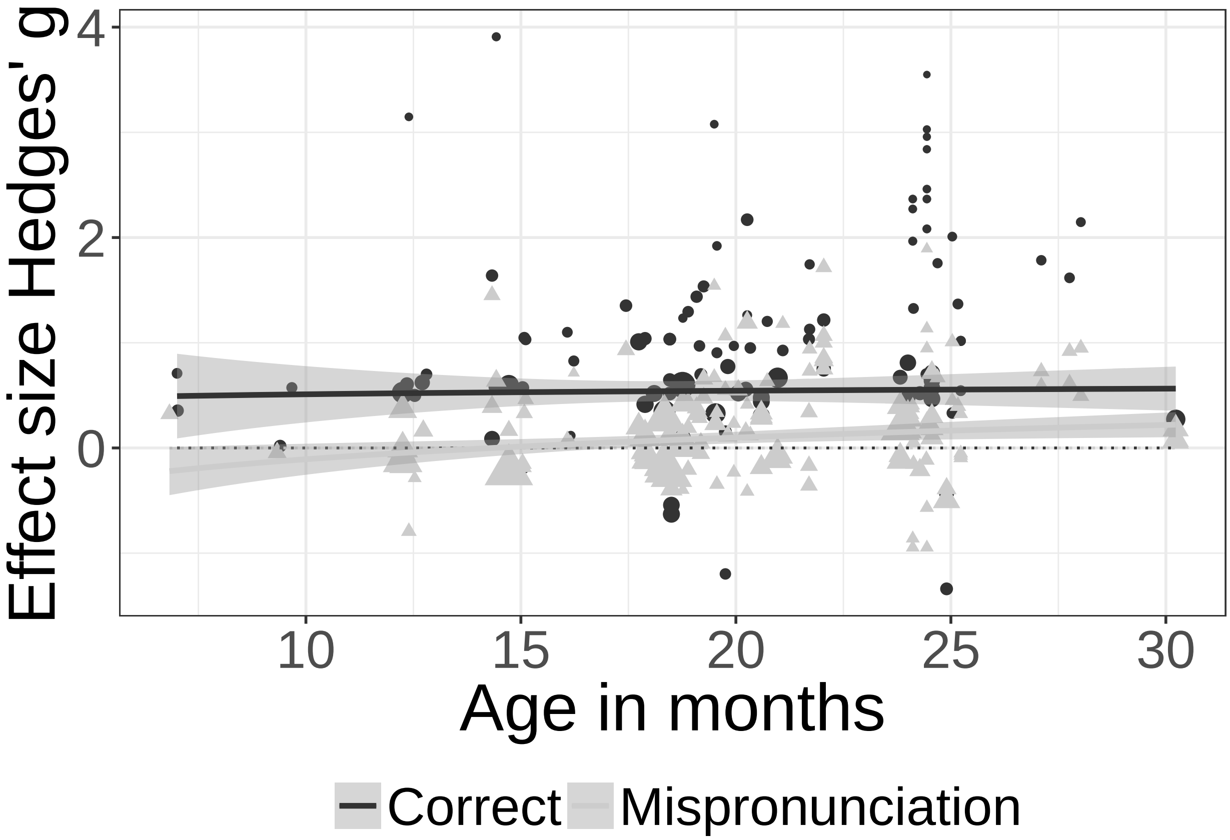
```
# ggsave('figures/AgeEffect_log.jpg', p,height= 7,width= 6)



jpeg(filename = "figures/AgeEffect_log.jpg", width = 600, height = 400, units = "px")

p

dev.off()
```

```
## pdf
##   2
```

Plot Mispronunciation Effect by Age (bw)

```
p <- ggplot(dat, aes(mean_age_1/30.44, g_calc, color = condition_label)) + geom_point(aes(size = weights
    shape = condition_label, color = condition_label), show.legend = FALSE) +
    geom_line(y = 0, linetype = "dotted") + geom_smooth(method = "lm", formula = y ~
    log(x), aes(weight = weights_g)) + scale_color_grey() + theme_bw() + theme(text = element_text(size
    legend.title = element_blank(), legend.position = "bottom") + xlab("Age in months") +
```

```
    ylab("Effect size Hedges' g")
p
```




```
ggsave("figures/AgeEffect_log_BW.jpg", p, height = 3, width = 6)
```

Correlation MP effect and Vocabulary

First, let's take a look at which vocabulary data we have available.

```
vocab_info <- db_ET_correct %>% mutate(has_vocab = ifelse(!is.na(r_comprehension),
    "comprehension", ifelse(!is.na(r_production), "production", "none"))) %>%
    group_by(has_vocab) %>% summarize(count = n())

kable(vocab_info)
```

has_vocab	count
comprehension	12
none	87
production	5

We have 17 correlations, roughly evenly divided between comprehension and production data. There is reason to believe that production data are different from comprehension data (the former being easier to estimate for parents in the typical questionnaire-based assessment), so we should both analyze this data separately and see whether it makes sense in a joint analysis.

```
# we're relying on the library meta function metacor
compr <- subset(db_ET_correct, !is.na(db_ET_correct$r_comprehension) & r_comprehension >
    -1)

metacor(cor = r_comprehension, n = n_1, studlab = short_cite, data = compr,
    sm = "COR")
```

```
##                                     COR            95%-CI %W(fixed)
## Zesiger et al. (2012)             0.0610 [-0.3553; 0.4773]       5.8
## Zesiger et al. (2012)            -0.1590 [-0.5663; 0.2483]       6.1
## Mani, Coleman, & Plunkett (2008)  0.0300 [-0.2271; 0.2871]      15.2
## Swingley & Aslin (2000)           0.1050 [-0.1564; 0.3664]      14.7
## Mani & Plunkett 2007             -0.1700 [-0.5234; 0.1834]       8.0
## Mani & Plunkett 2007             -0.1700 [-0.5175; 0.1775]       8.3
## Swingley & Aslin (2002)           0.1410 [-0.2432; 0.5252]       6.8
## Swingley & Aslin (2002)           0.1410 [-0.2596; 0.5416]       6.3
## Swingley 2003                     0.3400 [ 0.0470; 0.6330]      11.7
## Swingley 2003                     0.0600 [-0.3472; 0.4672]       6.1
## H\xbfjen et al.                   0.2220 [-0.2591; 0.7031]       4.3
## H\xbfjen et al.                   0.4820 [ 0.0935; 0.8705]       6.7
##                                  %W(random)
## Zesiger et al. (2012)                   6.2
## Zesiger et al. (2012)                   6.5
## Mani, Coleman, & Plunkett (2008)       13.7
## Swingley & Aslin (2000)                13.4
## Mani & Plunkett 2007                    8.3
## Mani & Plunkett 2007                    8.5
## Swingley & Aslin (2002)                 7.2
## Swingley & Aslin (2002)                 6.7
## Swingley 2003                          11.2
## Swingley 2003                           6.5
## H\xbfjen et al.                         4.8
## H\xbfjen et al.                         7.0
##
## Number of studies combined: k = 12
##
##                         COR            95%-CI    z p-value
## Fixed effect model   0.0897 [-0.0105; 0.1900] 1.75  0.0795
## Random effects model 0.0893 [-0.0212; 0.1999] 1.58  0.1132
##
## Quantifying heterogeneity:
## tau^2 = 0.0060; H = 1.09 [1.00; 1.50]; I^2 = 15.7% [0.0%; 55.4%]
##
## Test of heterogeneity:
##      Q d.f. p-value
##  13.05   11  0.2899
##
## Details on meta-analytical method:
## - Inverse variance method
## - DerSimonian-Laird estimator for tau^2
## - Untransformed correlations
```

```
# we're relying on the library meta function metacor
prodr <- subset(db_ET_correct, !is.na(db_ET_correct$r_production) & r_production <
```

```r
    1)

metacor(cor = r_production, n = n_1, studlab = short_cite, data = prodr, sm = "COR")
```

```
##                                       COR            95%-CI %W(fixed)
## Zesiger et al. (2012)             -0.0090 [-0.4268; 0.4088]       5.0
## Zesiger et al. (2012)             -0.1720 [-0.5775; 0.2335]       5.3
## Mani, Coleman, & Plunkett (2008)   0.0700 [-0.1861; 0.3261]      13.2
## Mani & Plunkett 2007              -0.1100 [-0.4696; 0.2496]       6.7
## Mani & Plunkett 2007              -0.1100 [-0.4635; 0.2435]       6.9
## Swingley & Aslin (2002)            0.1820 [-0.1970; 0.5610]       6.0
## Swingley & Aslin (2002)            0.1820 [-0.2131; 0.5771]       5.6
## Swingley 2003                      0.1800 [-0.1406; 0.5006]       8.4
## Swingley 2003                      0.0700 [-0.3367; 0.4767]       5.2
## Ramon-Casas et al. 2009            0.0980 [-0.3068; 0.5028]       5.3
## Ramon-Casas et al. 2009           -0.1470 [-0.5468; 0.2528]       5.4
## Ramon-Casas et al. 2009           -0.2300 [-0.6171; 0.1571]       5.8
## Ramon-Casas et al. 2009            0.2400 [-0.1451; 0.6251]       5.9
## Ramon-Casas et al. 2009            0.4350 [ 0.1037; 0.7663]       7.9
## H\xbfjen et al.                    0.2220 [-0.2591; 0.7031]       3.7
## H\xbfjen et al.                   -0.1480 [-0.6430; 0.3470]       3.5
##                                   %W(random)
## Zesiger et al. (2012)                    5.0
## Zesiger et al. (2012)                    5.3
## Mani, Coleman, & Plunkett (2008)        13.2
## Mani & Plunkett 2007                     6.7
## Mani & Plunkett 2007                     6.9
## Swingley & Aslin (2002)                  6.0
## Swingley & Aslin (2002)                  5.6
## Swingley 2003                            8.4
## Swingley 2003                            5.2
## Ramon-Casas et al. 2009                  5.3
## Ramon-Casas et al. 2009                  5.4
## Ramon-Casas et al. 2009                  5.8
## Ramon-Casas et al. 2009                  5.9
## Ramon-Casas et al. 2009                  7.9
## H\xbfjen et al.                          3.7
## H\xbfjen et al.                          3.5
##
## Number of studies combined: k = 16
##
##                         COR            95%-CI    z p-value
## Fixed effect model   0.0601 [-0.0331; 0.1533] 1.26  0.2061
## Random effects model 0.0601 [-0.0331; 0.1533] 1.26  0.2061
##
## Quantifying heterogeneity:
## tau^2 = 0; H = 1.00 [1.00; 1.42]; I^2 = 0.0% [0.0%; 50.7%]
##
## Test of heterogeneity:
##      Q d.f. p-value
##  14.51   15  0.4870
##
## Details on meta-analytical method:
## - Inverse variance method
```

```
## - DerSimonian-Laird estimator for tau^2
## - Untransformed correlations
```

Number of Features Changed

Number of features

Size of mispronunciation, measured in features changed

```r
db_ET_MPf <- subset(db_ET_MP, n_feature == "0" | n_feature == "1" | n_feature ==
    "2" | n_feature == "3")

# rma_NFeatures <- rma.mv(g_calc, g_var_calc, mods = ~as.ordered(n_feature),
# data = db_ET_MP, random = ~collapse | short_cite)
rma_NFeatures <- rma.mv(g_calc, g_var_calc, mods = ~as.factor(n_feature), data = db_ET_MPf,
    random = ~collapse | short_cite)


summary(rma_NFeatures)
```

```
##
## Multivariate Meta-Analysis Model (k = 121; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -60.2216  120.4431  130.4431  144.2965  130.9788
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 26)
## inner factor: collapse   (nlvls = 45)
##
##             estim    sqrt  fixed
## tau^2      0.1321  0.3635     no
## rho        0.4089             no
##
## Test for Residual Heterogeneity:
## QE(df = 118) = 389.3298, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3):
## QM(df = 2) = 4.9103, p-val = 0.0859
##
## Model Results:
##
##                        estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt                  0.2787  0.0664   4.1942  <.0001   0.1484   0.4089
## as.factor(n_feature)2   -0.0890  0.0809  -1.1006  0.2711  -0.2475   0.0695
## as.factor(n_feature)3   -0.2326  0.1059  -2.1971  0.0280  -0.4401  -0.0251
##
## intrcpt                ***
## as.factor(n_feature)2
## as.factor(n_feature)3    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Number of features subset to age range

Size of mispronunciation, measured in features changed

```r
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")

mf <- subset(dat_f, n_feature == "3")
min_age <- min(mf$mean_age_1)
max_age <- max(mf$mean_age_1)

dat_fage = dat_f %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

# rma_NFeatures <- rma.mv(g_calc, g_var_calc, mods = ~as.ordered(n_feature),
# data = db_ET_MP, random = ~collapse | short_cite)
rma_NFeatures_agesub <- rma.mv(g_calc, g_var_calc, mods = ~as.factor(n_feature),
    data = dat_f, random = ~collapse | short_cite)


summary(rma_NFeatures_agesub)
```

```
##
## Multivariate Meta-Analysis Model (k = 211; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -235.9905   471.9810   483.9810   503.9773   484.4010
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 27)
## inner factor: collapse   (nlvls = 49)
##
##             estim    sqrt  fixed
## tau^2      0.1565  0.3957     no
## rho        0.7047             no
##
## Test for Residual Heterogeneity:
## QE(df = 207) = 1010.2647, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 181.4363, p-val < .0001
##
## Model Results:
##
##                        estimate      se      zval    pval    ci.lb
## intrcpt                  0.7954  0.0775   10.2609  <.0001   0.6435
## as.factor(n_feature)1   -0.5093  0.0402  -12.6694  <.0001  -0.5880
## as.factor(n_feature)2   -0.4754  0.0731   -6.5000  <.0001  -0.6187
## as.factor(n_feature)3   -0.6942  0.1004   -6.9130  <.0001  -0.8910
##                          ci.ub
## intrcpt                 0.9473  ***
## as.factor(n_feature)1  -0.4305  ***
## as.factor(n_feature)2  -0.3321  ***
## as.factor(n_feature)3  -0.4974  ***
##
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Number of features with condition moderator

```r
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")

# rma_NFeatures <- rma.mv(g_calc, g_var_calc, mods = ~as.ordered(n_feature),
# data = db_ET_MP, random = ~collapse | short_cite)
rma_NFeatures <- rma.mv(g_calc, g_var_calc, mods = ~as.factor(n_feature) * condition,
    data = dat_f, random = ~collapse | short_cite)


summary(rma_NFeatures)
```

```
##
## Multivariate Meta-Analysis Model (k = 211; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -234.6537   469.3074   483.3074   506.6025   483.8730
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 27)
## inner factor: collapse   (nlvls = 49)
##
##             estim    sqrt  fixed
## tau^2      0.1530  0.3911     no
## rho        0.6938             no
##
## Test for Residual Heterogeneity:
## QE(df = 206) = 980.4970, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5):
## QM(df = 4) = 184.5957, p-val < .0001
##
## Model Results:
##
##                         estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt                   0.5966  0.1346   4.4341  <.0001   0.3329   0.8604
## as.factor(n_feature)1    -0.3195  0.1130  -2.8277  0.0047  -0.5409  -0.0980
## as.factor(n_feature)2    -0.2848  0.1290  -2.2078  0.0273  -0.5377  -0.0320
## as.factor(n_feature)3    -0.5037  0.1462  -3.4456  0.0006  -0.7902  -0.2172
## condition                 0.1906  0.1062   1.7949  0.0727  -0.0175   0.3987
##
## intrcpt                 ***
## as.factor(n_feature)1    **
## as.factor(n_feature)2     *
## as.factor(n_feature)3   ***
## condition                 .
##
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Number of features with age moderator

```r
db_ET_MPf <- subset(db_ET_MP, n_feature == "0" | n_feature == "1" | n_feature ==
    "2" | n_feature == "3")

rma_NFeaturesAge <- rma.mv(g_calc, g_var_calc, mods = ~as.factor(n_feature) *
    age.C, data = db_ET_MPf, random = ~collapse | short_cite)


summary(rma_NFeaturesAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 121; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -60.1851  120.3702  136.3702  158.3296  137.7287
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 26)
## inner factor: collapse   (nlvls = 45)
##
##             estim    sqrt  fixed
## tau^2      0.1338  0.3658     no
## rho        0.4108             no
##
## Test for Residual Heterogeneity:
## QE(df = 115) = 372.6874, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 5.8860, p-val = 0.3175
##
## Model Results:
##
##                              estimate      se     zval    pval    ci.lb
## intrcpt                        0.2824  0.0669   4.2187  <.0001   0.1512
## as.factor(n_feature)2         -0.0890  0.0815  -1.0921  0.2748  -0.2487
## as.factor(n_feature)3         -0.2227  0.1109  -2.0090  0.0445  -0.4400
## age.C                          0.0136  0.0150   0.9045  0.3657  -0.0158
## as.factor(n_feature)2:age.C    0.0019  0.0182   0.1054  0.9160  -0.0337
## as.factor(n_feature)3:age.C   -0.0066  0.0227  -0.2930  0.7696  -0.0511
##                                ci.ub
## intrcpt                       0.4136  ***
## as.factor(n_feature)2         0.0707
## as.factor(n_feature)3        -0.0054    *
## age.C                         0.0430
## as.factor(n_feature)2:age.C   0.0375
## as.factor(n_feature)3:age.C   0.0378
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Number of features with condition and age moderators

```
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")


rma_NFeaturesAge <- rma.mv(g_calc, g_var_calc, mods = ~as.factor(n_feature) *
    age.C * condition, data = dat_f, random = ~collapse | short_cite)


summary(rma_NFeaturesAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 211; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -232.6365   465.2730   489.2730   528.9127   490.9326
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 27)
## inner factor: collapse   (nlvls = 49)
##
##             estim    sqrt  fixed
## tau^2      0.1581  0.3976     no
## rho        0.7224             no
##
## Test for Residual Heterogeneity:
## QE(df = 201) = 956.3669, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8,9,10):
## QM(df = 9) = 190.4816, p-val < .0001
##
## Model Results:
##
##                               estimate      se     zval    pval    ci.lb
## intrcpt                         0.6099  0.1361   4.4828  <.0001   0.3433
## as.factor(n_feature)1          -0.3219  0.1132  -2.8421  0.0045  -0.5438
## as.factor(n_feature)2          -0.2920  0.1293  -2.2593  0.0239  -0.5453
## as.factor(n_feature)3          -0.5182  0.1497  -3.4617  0.0005  -0.8116
## age.C                           0.0842  0.0506   1.6637  0.0962  -0.0150
## condition                       0.1919  0.1063   1.8056  0.0710  -0.0164
## as.factor(n_feature)1:age.C    -0.0691  0.0488  -1.4153  0.1570  -0.1648
## as.factor(n_feature)2:age.C    -0.0486  0.0510  -0.9533  0.3404  -0.1485
## as.factor(n_feature)3:age.C    -0.0535  0.0526  -1.0173  0.3090  -0.1566
## age.C:condition                -0.0648  0.0481  -1.3465  0.1782  -0.1591
##                                  ci.ub
## intrcpt                         0.8766  ***
## as.factor(n_feature)1          -0.0999   **
## as.factor(n_feature)2          -0.0387    *
## as.factor(n_feature)3          -0.2248  ***
## age.C                           0.1835    .
## condition                       0.4003    .
## as.factor(n_feature)1:age.C     0.0266
```

```
## as.factor(n_feature)2:age.C   0.0513
## as.factor(n_feature)3:age.C   0.0496
## age.C:condition               0.0295
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Features changed with age moderator, subset to same age range

```
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")

mf <- subset(dat_f, n_feature == "3")
min_age <- min(mf$mean_age_1)
max_age <- max(mf$mean_age_1)

dat_fage = dat_f %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

rma_FeatureAgeS <- rma.mv(g_calc, g_var_calc, mods = ~age.C * as.factor(n_feature),
    data = dat_fage, random = ~collapse | short_cite)

summary(rma_FeatureAgeS)
```

```
##
## Multivariate Meta-Analysis Model (k = 174; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -173.0636   346.1271   366.1271   397.2470   367.5465
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 22)
## inner factor: collapse   (nlvls = 37)
##
##             estim    sqrt  fixed
## tau^2      0.1962  0.4430     no
## rho        0.8067             no
##
## Test for Residual Heterogeneity:
## QE(df = 166) = 798.7193, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8):
## QM(df = 7) = 138.8991, p-val < .0001
##
## Model Results:
##
##                              estimate      se     zval    pval    ci.lb
## intrcpt                        0.7936  0.1004   7.9071  <.0001   0.5969
## age.C                          0.0129  0.0204   0.6328  0.5268  -0.0271
## as.factor(n_feature)1         -0.4767  0.0481  -9.9073  <.0001  -0.5710
## as.factor(n_feature)2         -0.4072  0.0784  -5.1968  <.0001  -0.5608
## as.factor(n_feature)3         -0.6688  0.1068  -6.2602  <.0001  -0.8782
## age.C:as.factor(n_feature)1   -0.0203  0.0145  -1.4070  0.1594  -0.0487
```

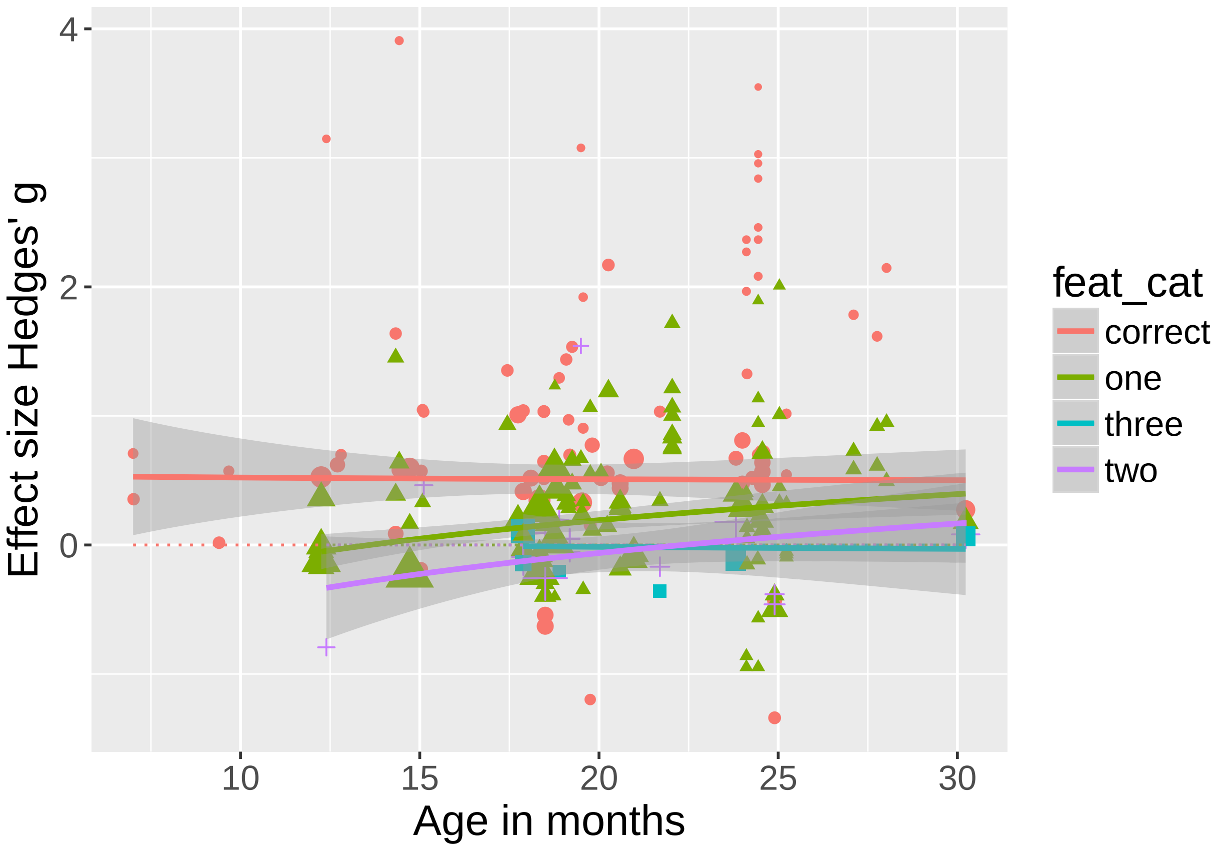
```
## age.C:as.factor(n_feature)2   -0.0133  0.0196  -0.6772  0.4983  -0.0518
## age.C:as.factor(n_feature)3   -0.0023  0.0223  -0.1045  0.9168  -0.0461
##                                ci.ub
## intrcpt                       0.9903  ***
## age.C                         0.0530
## as.factor(n_feature)1        -0.3824  ***
## as.factor(n_feature)2        -0.2536  ***
## as.factor(n_feature)3        -0.4594  ***
## age.C:as.factor(n_feature)1   0.0080
## age.C:as.factor(n_feature)2   0.0252
## age.C:as.factor(n_feature)3   0.0414
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# rma_FeatureS <- rma.mv(g_calc, g_var_calc, mods =
# ~condition*as.factor(n_feature), data = dat_fage, random = ~ collapse |
# short_cite)

# summary(rma_FeatureS)
```

Plotting number of Features Changed

Plot number of Features

```
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")

dat_f$feat_cat <- ifelse(dat_f$n_feature == 1, "one", ifelse(dat_f$n_feature ==
    2, "two", ifelse(dat_f$n_feature == 3, "three", ifelse(dat_f$n_feature ==
    0, "correct", "none"))))

dat_f <- subset(dat_f, feat_cat != "none")


p <- ggplot(dat_f, aes(mean_age_1/30.44, g_calc, color = feat_cat)) + geom_point(aes(size = weights_g,
    shape = feat_cat), show.legend = FALSE) + # facet_grid(.~type_feature)+
geom_line(y = 0, linetype = "dotted") + geom_smooth(method = "lm", formula = y ~
    log(x), aes(weight = weights_g)) + theme(text = element_text(size = 16)) +
    xlab("Age in months") + ylab("Effect size Hedges' g")
p
```

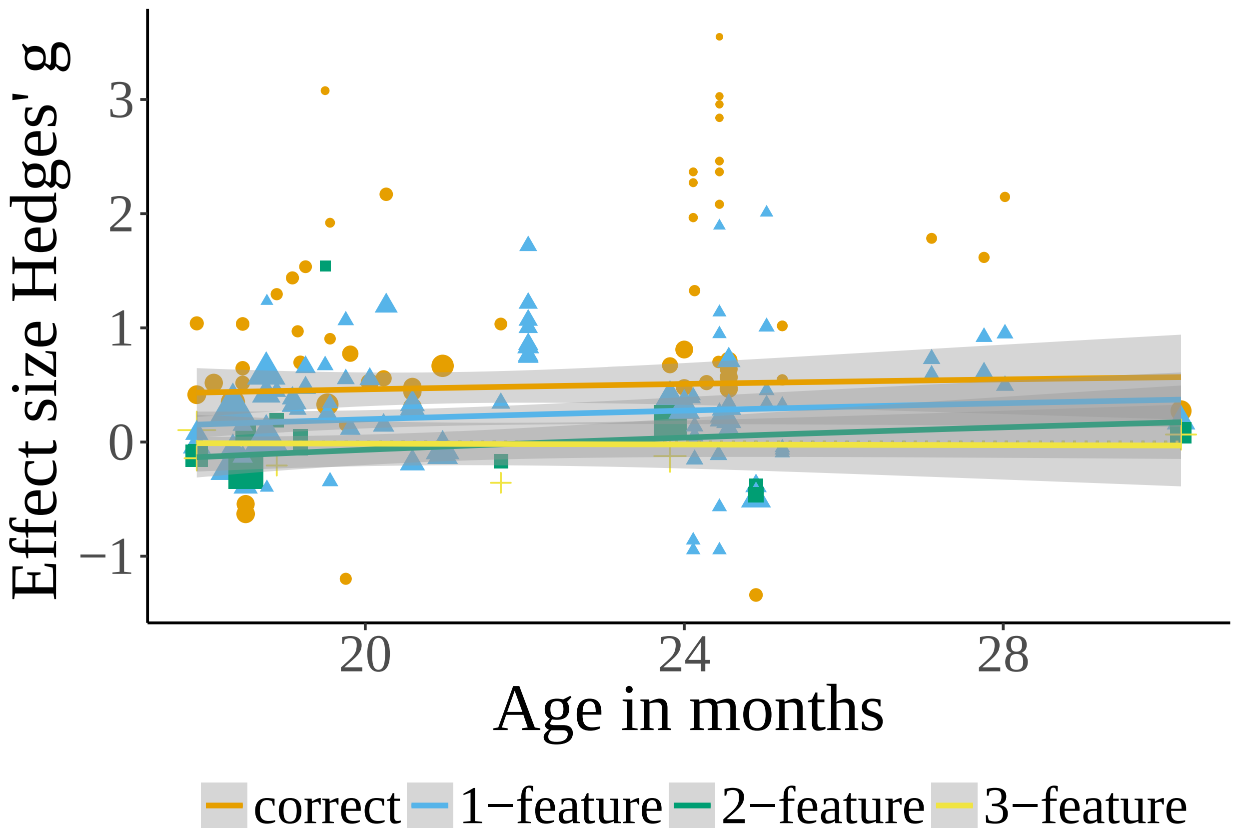



```r
ggsave("figures/AgeEffect_log_feat.jpg", p)
```

Plot number of Features subsetted for age

```r
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")

mf <- subset(dat_f, n_feature == "3")
min_age <- min(mf$mean_age_1)
max_age <- max(mf$mean_age_1)

dat_fage = dat_f %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

dat_fage$feat_cat <- ifelse(dat_fage$n_feature == 1, "1-feature", ifelse(dat_fage$n_feature ==
    2, "2-feature", ifelse(dat_fage$n_feature == 3, "3-feature", ifelse(dat_fage$n_feature ==
    0, "correct", "none"))))

dat_fage <- subset(dat_fage, feat_cat != "none")

dat_fage$Features_changed <- factor(dat_fage$feat_cat, levels = c("correct",
    "1-feature", "2-feature", "3-feature"))

# Color Blind palette:
cbPalette <- c("#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "#D55E00",
    "#CC79A7")
```

```r
p <- ggplot(dat_fage, aes(mean_age_1/30.44, g_calc, color = Features_changed)) +
    geom_point(aes(size = weights_g, shape = Features_changed), show.legend = FALSE) +
    # facet_grid(.~type_feature)+
scale_colour_manual(values = cbPalette) + geom_line(y = 0, linetype = "dotted") +
    geom_smooth(method = "lm", formula = y ~ log(x), aes(weight = weights_g)) +
    apatheme + theme(legend.title = element_blank(), legend.position = "bottom") +
    xlab("Age in months") + ylab("Effect size Hedges' g")
p
```

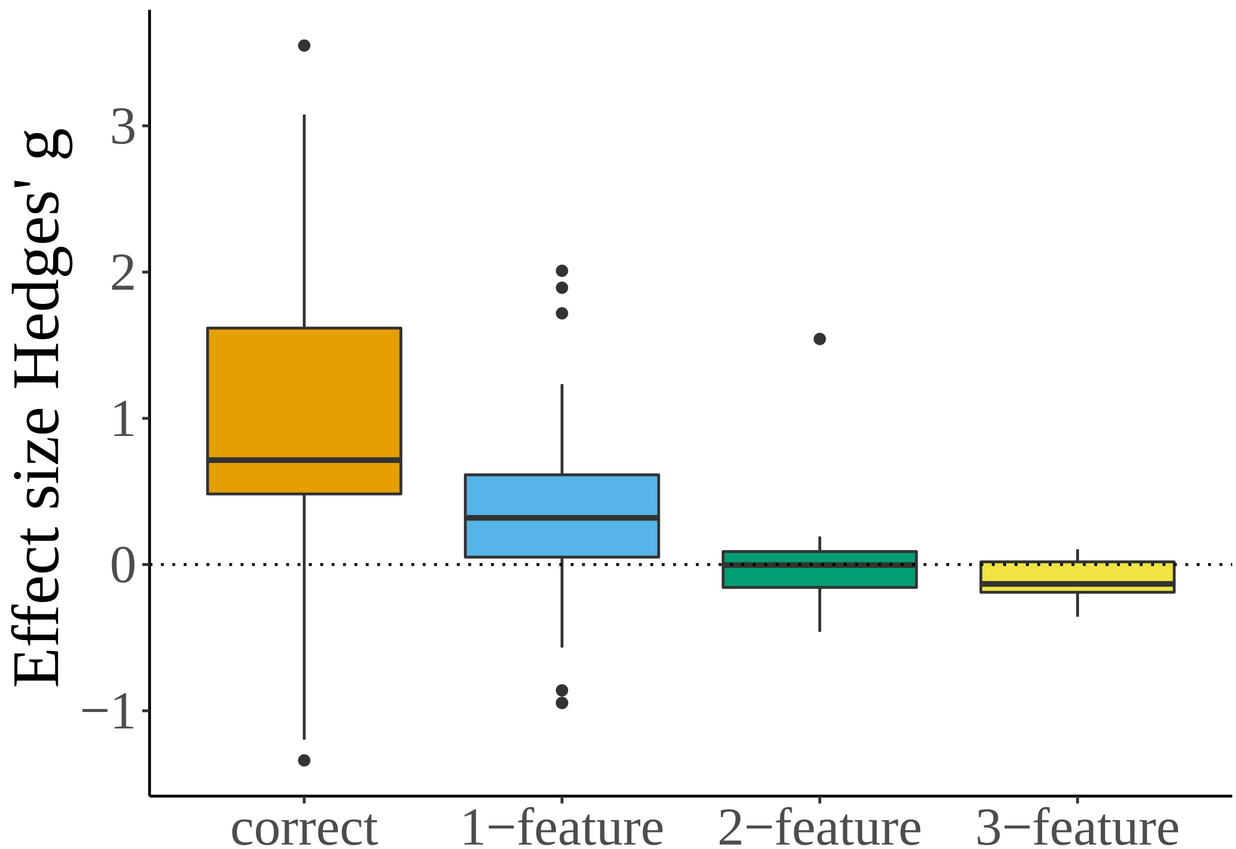



```r
ggsave("figures/AgeEffect_log_feat_agesub.jpg", p)
```

Plot number of Features subsetted for age Boxplot

```r
dat_f <- subset(dat, n_feature == "0" | n_feature == "1" | n_feature == "2" |
    n_feature == "3")

mf <- subset(dat_f, n_feature == "3")
min_age <- min(mf$mean_age_1)
max_age <- max(mf$mean_age_1)

dat_fage = dat_f %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

dat_fage$feat_cat <- ifelse(dat_fage$n_feature == 1, "1-feature", ifelse(dat_fage$n_feature ==
    2, "2-feature", ifelse(dat_fage$n_feature == 3, "3-feature", ifelse(dat_fage$n_feature ==
    0, "correct", "none"))))
```

```
dat_fage <- subset(dat_fage, feat_cat != "none")

dat_fage$Features_changed <- factor(dat_fage$feat_cat, levels = c("correct",
    "1-feature", "2-feature", "3-feature"))

# Color Blind palette:
cbPalette <- c("#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "#D55E00",
    "#CC79A7")

p <- ggplot(dat_fage, aes(Features_changed, g_calc, fill = Features_changed)) +
    geom_boxplot() + # geom_smooth(method = 'lm', formula = y ~ log(x), aes(weight=weights_g)) +
scale_fill_manual(values = cbPalette) + apatheme + theme(text = element_text(size = 25),
    legend.title = element_blank(), legend.position = "none", axis.title.x = element_blank()) +
    # xlab('Number of Features Changed') +
geom_hline(yintercept = 0, linetype = "dotted") + ylab("Effect size Hedges' g")

p
```




```
ggsave("figures/AgeEffect_log_feat_agesub_noage.jpg", p)
```

Type of MP: Vowel, consonant, or tone

Type of MP: Vowel, consonant, or tone

```
db_MP_type <- subset(db_ET_MP, type_feature == "consonant" | type_feature ==
    "vowel")



rma_TypeFeaturesMP <- rma.mv(g_calc, g_var_calc, mods = ~type_feature, data = db_MP_type,
    random = ~collapse | short_cite)


summary(rma_TypeFeaturesMP)
```

```
##
## Multivariate Meta-Analysis Model (k = 133; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -64.0402  128.0804  136.0804  147.5812  136.3979
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 26)
## inner factor: collapse   (nlvls = 46)
##
##             estim    sqrt  fixed
## tau^2      0.1263  0.3553     no
## rho        0.5620             no
##
## Test for Residual Heterogeneity:
## QE(df = 131) = 427.6655, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.1467, p-val = 0.7017
##
## Model Results:
##
##                    estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt              0.2262  0.0729  3.1022  0.0019   0.0833  0.3691  **
## type_featurevowel    0.0338  0.0881  0.3830  0.7017  -0.1390  0.2065
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Type of MP: Vowel, consonant, or tone with age moderator

```
db_MP_type <- subset(db_ET_MP, type_feature == "consonant" | type_feature ==
    "vowel")


rma_TypeFeaturesMPAge <- rma.mv(g_calc, g_var_calc, mods = ~type_feature * age.C,
```

```
    data = db_MP_type, random = ~collapse | short_cite)


summary(rma_TypeFeaturesMPAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 133; method: REML)
##
##    logLik  Deviance       AIC       BIC      AICc
## -62.8963  125.7927  137.7927  154.9515  138.4812
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 26)
## inner factor: collapse   (nlvls = 46)
##
##             estim    sqrt  fixed
## tau^2      0.1274  0.3570     no
## rho        0.5445             no
##
## Test for Residual Heterogeneity:
## QE(df = 129) = 415.3869, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 1.5441, p-val = 0.6721
##
## Model Results:
##
##                          estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                    0.2283  0.0731  3.1237  0.0018   0.0851  0.3716
## type_featurevowel          0.0439  0.0889  0.4945  0.6210  -0.1302  0.2181
## age.C                      0.0143  0.0147  0.9676  0.3332  -0.0146  0.0431
## type_featurevowel:age.C    0.0008  0.0171  0.0484  0.9614  -0.0327  0.0344
##
## intrcpt                  **
## type_featurevowel
## age.C
## type_featurevowel:age.C
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Type of MP: Vowel, consonant, or tone with condition moderator

```
dat_type <- subset(dat, type_feature == "consonant" | type_feature == "vowel" |
    type_feature == "tone")
dat_type$type_feature <- as.factor(ifelse(dat_type$condition == 1, "none", dat_type$type_feature))


rma_TypeFeatures <- rma.mv(g_calc, g_var_calc, mods = ~relevel(type_feature,
    "none") * condition, data = dat_type, random = ~collapse | short_cite)
```

```r
summary(rma_TypeFeatures)
```

```
##
## Multivariate Meta-Analysis Model (k = 228; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -236.8091   473.6183   485.6183   506.0882   486.0054
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 28)
## inner factor: collapse   (nlvls = 46)
##
##             estim    sqrt  fixed
## tau^2      0.1238  0.3519     no
## rho        0.6901             no
##
## Test for Residual Heterogeneity:
## QE(df = 224) = 981.7485, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 154.6077, p-val < .0001
##
## Model Results:
##
##                                 estimate      se      zval    pval
## intrcpt                           0.7114  0.0688   10.3387  <.0001
## relevel(type_feature, "none")1   -0.4417  0.0423  -10.4486  <.0001
## relevel(type_feature, "none")4   -0.6356  0.1549   -4.1033  <.0001
## relevel(type_feature, "none")5   -0.4680  0.0565   -8.2812  <.0001
##                                   ci.lb    ci.ub
## intrcpt                          0.5765   0.8462  ***
## relevel(type_feature, "none")1  -0.5245  -0.3588  ***
## relevel(type_feature, "none")4  -0.9391  -0.3320  ***
## relevel(type_feature, "none")5  -0.5788  -0.3572  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Type of MP: Vowel, consonant, or tone with age and condition moderator

```r
dat_type <- subset(dat, type_feature == "consonant" | type_feature == "vowel" |
    type_feature == "tone")
dat_type$type_feature <- as.factor(ifelse(dat_type$condition == 1, "none", dat_type$type_feature))


rma_TypeFeaturesAge <- rma.mv(g_calc, g_var_calc, mods = ~relevel(type_feature,
    "none") * age.C * condition, data = dat_type, random = ~collapse | short_cite)


summary(rma_TypeFeaturesAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 228; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -234.9545   469.9090   489.9090   523.8452   490.9616
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 28)
## inner factor: collapse   (nlvls = 46)
##
##             estim    sqrt  fixed
## tau^2      0.1260  0.3549     no
## rho        0.6767             no
##
## Test for Residual Heterogeneity:
## QE(df = 220) = 967.8211, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8):
## QM(df = 7) = 158.2894, p-val < .0001
##
## Model Results:
##
##                                      estimate      se      zval    pval
## intrcpt                                0.7276  0.0702   10.3680  <.0001
## relevel(type_feature, "none")1        -0.4489  0.0427  -10.5083  <.0001
## relevel(type_feature, "none")4        -0.6202  0.1703   -3.6419  0.0003
## relevel(type_feature, "none")5        -0.4874  0.0630   -7.7322  <.0001
## age.C                                  0.0161  0.0124    1.2981  0.1942
## relevel(type_feature, "none")1:age.C   0.0076  0.0104    0.7309  0.4648
## relevel(type_feature, "none")4:age.C   0.0055  0.0311    0.1770  0.8595
## relevel(type_feature, "none")5:age.C  -0.0082  0.0114   -0.7146  0.4748
##                                        ci.lb    ci.ub
## intrcpt                               0.5901   0.8652  ***
## relevel(type_feature, "none")1       -0.5327  -0.3652  ***
## relevel(type_feature, "none")4       -0.9540  -0.2864  ***
## relevel(type_feature, "none")5       -0.6110  -0.3639  ***
## age.C                                -0.0082   0.0405
## relevel(type_feature, "none")1:age.C -0.0128   0.0279
## relevel(type_feature, "none")4:age.C -0.0555   0.0665
## relevel(type_feature, "none")5:age.C -0.0306   0.0142
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Type of MP with language family moderator

```
# dat_type <- subset(dat, type_feature == 'consonant' | type_feature ==
# 'vowel' | type_feature == 'tone')

dat_type <- subset(dat, type_feature == "consonant" | type_feature == "vowel")

dat_type$type_feature <- as.factor(ifelse(dat_type$condition == 1, "none", dat_type$type_feature))
```

```r
dat_type$lang_family = ifelse(dat_type$native_lang == "American English" | dat_type$native_lang ==
    "British English" | dat_type$native_lang == "Dutch" | dat_type$native_lang ==
    "Danish" | dat_type$native_lang == "Swedish" | dat_type$native_lang == "English" |
    dat_type$native_lang == "German", "Germanic", ifelse(dat_type$native_lang ==
    "French" | dat_type$native_lang == "Catalan" | dat_type$native_lang == "Spanish" |
    dat_type$native_lang == "Catalan-Spanish" | dat_type$native_lang == "Swiss French",
    "Romanic", "Sino-Tibetian"))

dat_type_sub <- subset(dat_type, lang_family != "Sino-Tibetian")

rma_TypeFeatures_Lang <- rma.mv(g_calc, g_var_calc, mods = ~relevel(type_feature,
    "none") * lang_family, data = dat_type_sub, random = ~collapse | short_cite)


summary(rma_TypeFeatures_Lang)
```

```
##
## Multivariate Meta-Analysis Model (k = 212; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -226.0585   452.1170   468.1170   494.7400   468.8480
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 25)
## inner factor: collapse   (nlvls = 44)
##
##              estim    sqrt  fixed
## tau^2       0.1293  0.3596     no
## rho         0.5788             no
##
## Test for Residual Heterogeneity:
## QE(df = 206) = 893.9789, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 158.2471, p-val < .0001
##
## Model Results:
##
##                                                    estimate      se
## intrcpt                                              0.6597  0.0777
## relevel(type_feature, "none")1                      -0.4135  0.0441
## relevel(type_feature, "none")5                      -0.4830  0.0640
## lang_familyRomanic                                   0.4502  0.1801
## relevel(type_feature, "none")1:lang_familyRomanic   -0.6549  0.2157
## relevel(type_feature, "none")5:lang_familyRomanic    0.0924  0.1490
##                                                       zval    pval
## intrcpt                                             8.4880  <.0001
## relevel(type_feature, "none")1                     -9.3845  <.0001
## relevel(type_feature, "none")5                     -7.5453  <.0001
## lang_familyRomanic                                  2.4991  0.0124
## relevel(type_feature, "none")1:lang_familyRomanic  -3.0359  0.0024
## relevel(type_feature, "none")5:lang_familyRomanic   0.6202  0.5351
```

```
##                                                       ci.lb    ci.ub
## intrcpt                                              0.5073   0.8120  ***
## relevel(type_feature, "none")1                      -0.4998  -0.3271  ***
## relevel(type_feature, "none")5                      -0.6084  -0.3575  ***
## lang_familyRomanic                                   0.0971   0.8032    *
## relevel(type_feature, "none")1:lang_familyRomanic  -1.0777  -0.2321   **
## relevel(type_feature, "none")5:lang_familyRomanic  -0.1996   0.3843
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Type of MP with language family and condition moderators

```
dat_type <- subset(dat, type_feature == "consonant" | type_feature == "vowel")  # |
# type_feature == 'tone')
dat_type$type_feature <- as.factor(ifelse(dat_type$condition == 1, "none", dat_type$type_feature))

dat_type$lang_family = ifelse(dat_type$native_lang == "American English" | dat_type$native_lang ==
    "British English" | dat_type$native_lang == "Dutch" | dat_type$native_lang ==
    "Danish" | dat_type$native_lang == "Swedish" | dat_type$native_lang == "English" |
    dat_type$native_lang == "German", "Germanic", ifelse(dat_type$native_lang ==
    "French" | dat_type$native_lang == "Catalan" | dat_type$native_lang == "Spanish" |
    dat_type$native_lang == "Catalan-Spanish" | dat_type$native_lang == "Swiss French",
    "Romanic", "Sino-Tibetian"))

dat_type_sub <- subset(dat_type, lang_family != "Sino-Tibetian")
dat_type_sub$lang_family <- as.factor(dat_type_sub$lang_family)



rma_TypeFeatures_Lang <- rma.mv(g_calc, g_var_calc, mods = ~relevel(type_feature,
    "none") * lang_family * condition, data = dat_type_sub, random = ~collapse |
    short_cite)


summary(rma_TypeFeatures_Lang)
```

```
##
## Multivariate Meta-Analysis Model (k = 212; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -226.0585   452.1170   468.1170   494.7400   468.8480
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 25)
## inner factor: collapse   (nlvls = 44)
##
##             estim    sqrt  fixed
## tau^2      0.1293  0.3596     no
## rho        0.5788             no
##
## Test for Residual Heterogeneity:
```

```
## QE(df = 206) = 893.9789, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 158.2471, p-val < .0001
##
## Model Results:
##
##                                                     estimate      se
## intrcpt                                               0.6597  0.0777
## relevel(type_feature, "none")1                       -0.4135  0.0441
## relevel(type_feature, "none")5                       -0.4830  0.0640
## lang_familyRomanic                                    0.4502  0.1801
## relevel(type_feature, "none")1:lang_familyRomanic   -0.6549  0.2157
## relevel(type_feature, "none")5:lang_familyRomanic    0.0924  0.1490
##                                                        zval    pval
## intrcpt                                              8.4880  <.0001
## relevel(type_feature, "none")1                      -9.3845  <.0001
## relevel(type_feature, "none")5                      -7.5453  <.0001
## lang_familyRomanic                                   2.4991  0.0124
## relevel(type_feature, "none")1:lang_familyRomanic   -3.0359  0.0024
## relevel(type_feature, "none")5:lang_familyRomanic    0.6202  0.5351
##                                                       ci.lb    ci.ub
## intrcpt                                              0.5073   0.8120  ***
## relevel(type_feature, "none")1                      -0.4998  -0.3271  ***
## relevel(type_feature, "none")5                      -0.6084  -0.3575  ***
## lang_familyRomanic                                   0.0971   0.8032    *
## relevel(type_feature, "none")1:lang_familyRomanic   -1.0777  -0.2321   **
## relevel(type_feature, "none")5:lang_familyRomanic   -0.1996   0.3843
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting MP type: Consonant, Vowel, or Tone?

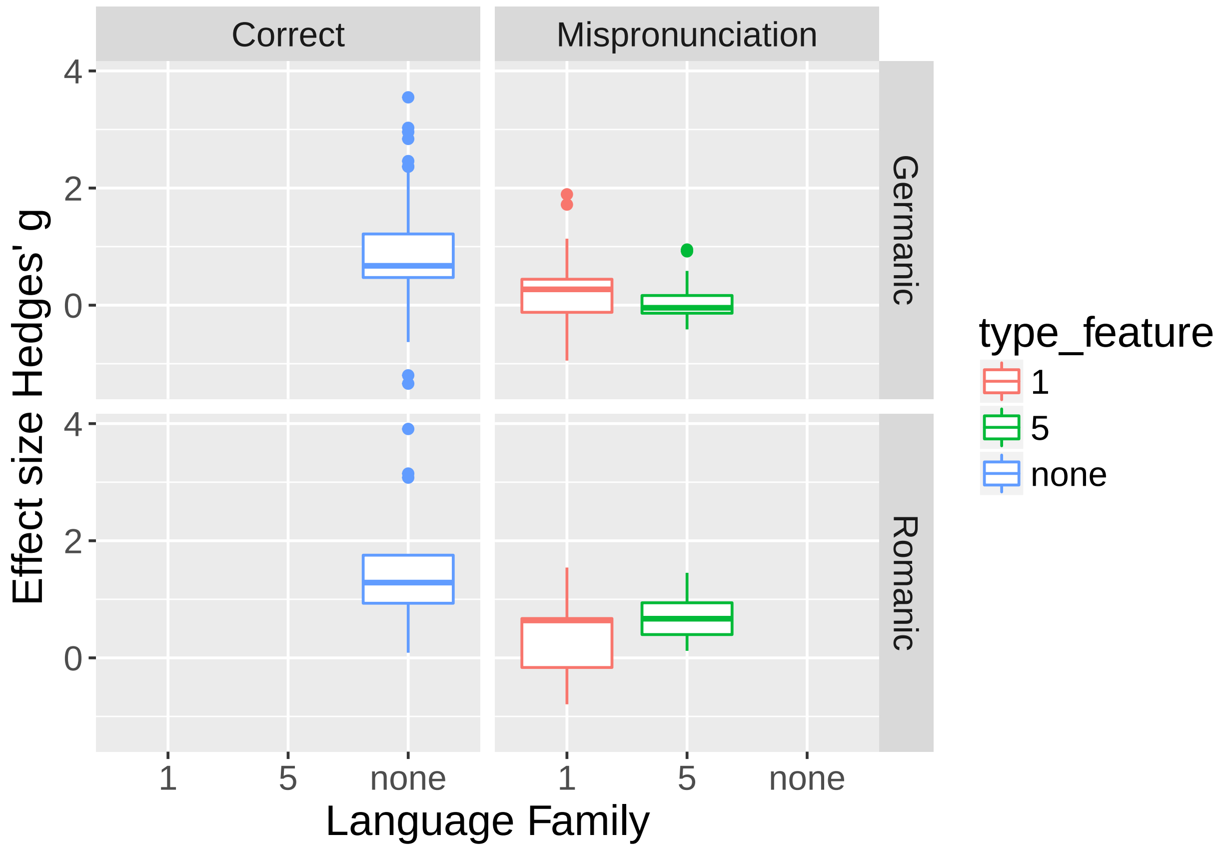
Plot MP type: Consonant, Vowel, or Tone?

```
p <- ggplot(dat, aes(mean_age_1/30.44, g_calc, color = condition_label)) + geom_point(aes(size = weights
    shape = type_feature), show.legend = FALSE) + facet_grid(. ~ type_feature) +
    geom_line(y = 0, linetype = "dotted") + geom_smooth(method = "lm", formula = y ~
    log(x), aes(weight = weights_g)) + theme(text = element_text(size = 16)) +
    xlab("Age in months") + ylab("Effect size Hedges' g")
p
```


```
ggsave("figures/AgeEffect_log_CV.jpg", p)
```

Plot Language Family by MP type: Consonant, Vowel, or Tone?

```
p <- ggplot(dat_type_sub, aes(type_feature, g_calc, color = type_feature)) +
    geom_boxplot() + facet_grid(lang_family ~ condition_label) + # geom_line(y= 0, linetype='dotted') +
# y ~ log(x), aes(weight=weights_g)) +
theme(text = element_text(size = 16)) + xlab("Language Family") + ylab("Effect size Hedges' g")
p
```




```
ggsave("figures/LangFamily_CV.jpg", p)
```

Distractor Familiarity (familiary, unfamiliar)

```
rma_Distractor <- rma.mv(g_calc, g_var_calc, mods = ~as.factor(object_pair),
    data = dat, random = ~collapse | short_cite)

summary(rma_Distractor)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -358.9670   717.9341   725.9341   740.0039   726.0980
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1428  0.3778     no
## rho        0.7418             no
##
## Test for Residual Heterogeneity:
## QE(df = 249) = 1349.9968, p-val < .0001
```

```
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 1.1294, p-val = 0.2879
##
## Model Results:
##
##                                      estimate      se     zval    pval
## intrcpt                                0.5036  0.0746   6.7468  <.0001
## as.factor(object_pair)familiar_novel  -0.1357  0.1277  -1.0627  0.2879
##                                        ci.lb   ci.ub
## intrcpt                               0.3573  0.6499  ***
## as.factor(object_pair)familiar_novel  -0.3860  0.1146
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Familiarity with condition moderator

```
rma_Distractor <- rma.mv(g_calc, g_var_calc, mods = ~condition * as.factor(object_pair),
    data = dat, random = ~collapse | short_cite)

summary(rma_Distractor)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -250.6056   501.2111   513.2111   534.2675   513.5611
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1410  0.3754     no
## rho        0.7375             no
##
## Test for Residual Heterogeneity:
## QE(df = 247) = 1085.1211, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 219.4592, p-val < .0001
##
## Model Results:
##
##                                                estimate      se     zval
## intrcpt                                          0.3230  0.0757   4.2641
## condition                                        0.4629  0.0384  12.0679
## as.factor(object_pair)familiar_novel            -0.1523  0.1300  -1.1711
## condition:as.factor(object_pair)familiar_novel   0.1411  0.0806   1.7510
##                                                  pval    ci.lb   ci.ub
## intrcpt                                        <.0001   0.1745  0.4714
```

```
## condition                                        <.0001   0.3877  0.5381
## as.factor(object_pair)familiar_novel             0.2416  -0.4072  0.1026
## condition:as.factor(object_pair)familiar_novel   0.0799  -0.0168  0.2991
##
## intrcpt                                          ***
## condition                                        ***
## as.factor(object_pair)familiar_novel
## condition:as.factor(object_pair)familiar_novel     .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Familiarity with age moderator

```r
rma_DistractorAge <- rma.mv(g_calc, g_var_calc, mods = ~age.C * as.factor(object_pair),
    data = dat, random = ~collapse | short_cite)

summary(rma_DistractorAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -355.6498   711.2996   723.2996   744.3559   723.6496
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1395  0.3735     no
## rho        0.7265             no
##
## Test for Residual Heterogeneity:
## QE(df = 247) = 1326.8487, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 4.9682, p-val = 0.1741
##
## Model Results:
##
##                                             estimate      se     zval
## intrcpt                                       0.5503  0.0778   7.0694
## age.C                                         0.0236  0.0134   1.7615
## as.factor(object_pair)familiar_novel         -0.2292  0.1459  -1.5711
## age.C:as.factor(object_pair)familiar_novel   -0.0007  0.0285  -0.0230
##                                               pval    ci.lb   ci.ub
## intrcpt                                     <.0001   0.3977  0.7029  ***
## age.C                                       0.0782  -0.0027  0.0499    .
## as.factor(object_pair)familiar_novel        0.1162  -0.5150  0.0567
## age.C:as.factor(object_pair)familiar_novel  0.9817  -0.0565  0.0551
##
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Familiarity with age and condition moderators

```
rma_DistractorAge <- rma.mv(g_calc, g_var_calc, mods = ~age.C * condition *
    as.factor(object_pair), data = dat, random = ~collapse | short_cite)

summary(rma_DistractorAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -247.3148   494.6296   514.6296   549.5602   515.5778
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1357  0.3684     no
## rho        0.7175             no
##
## Test for Residual Heterogeneity:
## QE(df = 243) = 1064.6022, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8):
## QM(df = 7) = 224.9573, p-val < .0001
##
## Model Results:
##
##                                                        estimate      se
## intrcpt                                                  0.3698  0.0785
## age.C                                                    0.0242  0.0138
## condition                                                0.4666  0.0415
## as.factor(object_pair)familiar_novel                    -0.2541  0.1471
## age.C:condition                                          0.0020  0.0092
## age.C:as.factor(object_pair)familiar_novel               0.0038  0.0288
## condition:as.factor(object_pair)familiar_novel           0.1755  0.0894
## age.C:condition:as.factor(object_pair)familiar_novel   -0.0203  0.0198
##                                                           zval    pval
## intrcpt                                                 4.7107  <.0001
## age.C                                                   1.7481  0.0804
## condition                                              11.2325  <.0001
## as.factor(object_pair)familiar_novel                   -1.7273  0.0841
## age.C:condition                                         0.2153  0.8295
## age.C:as.factor(object_pair)familiar_novel              0.1312  0.8956
## condition:as.factor(object_pair)familiar_novel          1.9637  0.0496
## age.C:condition:as.factor(object_pair)familiar_novel  -1.0267  0.3046
##                                                          ci.lb   ci.ub
## intrcpt                                                 0.2160  0.5237  ***
```

```
## age.C                                              -0.0029  0.0512    .
## condition                                           0.3852  0.5480  ***
## as.factor(object_pair)familiar_novel               -0.5425  0.0342    .
## age.C:condition                                    -0.0161  0.0201
## age.C:as.factor(object_pair)familiar_novel         -0.0526  0.0602
## condition:as.factor(object_pair)familiar_novel      0.0003  0.3507    *
## age.C:condition:as.factor(object_pair)familiar_novel  -0.0590  0.0184
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Familiarity with condition moderator, subset to same age range

```r
mf <- subset(dat, object_pair == "familiar_novel")
min_age <- min(mf$mean_age_1)

mf <- subset(dat, object_pair == "familiar_familiar")
max_age <- max(mf$mean_age_1)

dat_age = dat %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

rma_DistractorAgeS <- rma.mv(g_calc, g_var_calc, mods = ~condition * as.factor(object_pair),
    data = dat_age, random = ~collapse | short_cite)

summary(rma_DistractorAgeS)
```

```
##
## Multivariate Meta-Analysis Model (k = 186; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -178.9911   357.9823   369.9823   389.2063   370.4623
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 23)
## inner factor: collapse   (nlvls = 38)
##
##             estim    sqrt  fixed
## tau^2      0.1710  0.4136     no
## rho        0.7832             no
##
## Test for Residual Heterogeneity:
## QE(df = 182) = 822.0736, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 150.3023, p-val < .0001
##
## Model Results:
##
##                                                 estimate      se     zval
## intrcpt                                           0.3836  0.0989   3.8784
## condition                                         0.4293  0.0457   9.3896
## as.factor(object_pair)familiar_novel             -0.2677  0.1549  -1.7278
```

```
## condition:as.factor(object_pair)familiar_novel    0.1852  0.0914   2.0258
##                                                    pval    ci.lb   ci.ub
## intrcpt                                          0.0001   0.1897  0.5774
## condition                                        <.0001   0.3397  0.5189
## as.factor(object_pair)familiar_novel             0.0840  -0.5713  0.0360
## condition:as.factor(object_pair)familiar_novel  0.0428   0.0060  0.3644
##
## intrcpt                                          ***
## condition                                        ***
## as.factor(object_pair)familiar_novel               .
## condition:as.factor(object_pair)familiar_novel    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Familiarity with age and condition moderator, subset to same age range

```
mf <- subset(dat, object_pair == "familiar_novel")
min_age <- min(mf$mean_age_1)

mf <- subset(dat, object_pair == "familiar_familiar")
max_age <- max(mf$mean_age_1)

dat_age = dat %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

rma_DistractorAgeS <- rma.mv(g_calc, g_var_calc, mods = ~age.C * condition *
    as.factor(object_pair), data = dat_age, random = ~collapse | short_cite)

summary(rma_DistractorAgeS)
```

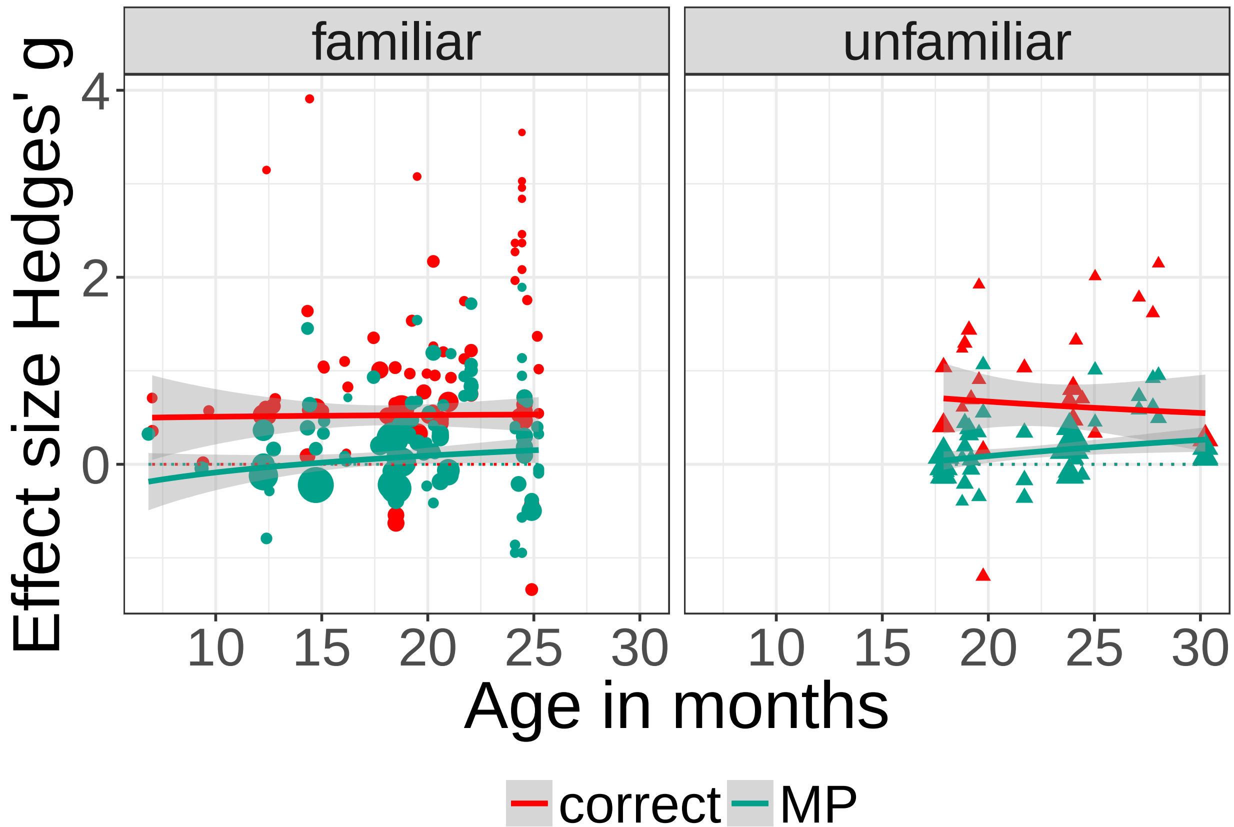
```
##
## Multivariate Meta-Analysis Model (k = 186; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -175.4351   350.8702   370.8702   402.6880   372.1876
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 23)
## inner factor: collapse   (nlvls = 38)
##
##             estim    sqrt  fixed
## tau^2      0.1749  0.4182     no
## rho        0.7669             no
##
## Test for Residual Heterogeneity:
## QE(df = 178) = 805.9230, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8):
## QM(df = 7) = 156.8377, p-val < .0001
##
## Model Results:
##
```

```
##                                                        estimate      se
## intrcpt                                                  0.3932  0.1012
## age.C                                                   -0.0130  0.0257
## condition                                                0.4087  0.0465
## as.factor(object_pair)familiar_novel                    -0.2981  0.1695
## age.C:condition                                          0.0448  0.0188
## age.C:as.factor(object_pair)familiar_novel               0.0350  0.0429
## condition:as.factor(object_pair)familiar_novel           0.2157  0.0927
## age.C:condition:as.factor(object_pair)familiar_novel    -0.0673  0.0351
##                                                           zval    pval
## intrcpt                                                 3.8857  0.0001
## age.C                                                  -0.5060  0.6128
## condition                                               8.7836  <.0001
## as.factor(object_pair)familiar_novel                   -1.7583  0.0787
## age.C:condition                                         2.3794  0.0173
## age.C:as.factor(object_pair)familiar_novel              0.8145  0.4153
## condition:as.factor(object_pair)familiar_novel          2.3270  0.0200
## age.C:condition:as.factor(object_pair)familiar_novel   -1.9158  0.0554
##                                                          ci.lb   ci.ub
## intrcpt                                                 0.1949  0.5915  ***
## age.C                                                  -0.0633  0.0373
## condition                                               0.3175  0.4999  ***
## as.factor(object_pair)familiar_novel                   -0.6303  0.0342    .
## age.C:condition                                         0.0079  0.0817    *
## age.C:as.factor(object_pair)familiar_novel             -0.0492  0.1192
## condition:as.factor(object_pair)familiar_novel          0.0340  0.3974    *
## age.C:condition:as.factor(object_pair)familiar_novel   -0.1362  0.0016    .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting Distractor Familiarity

Plot Distractor Familiarity

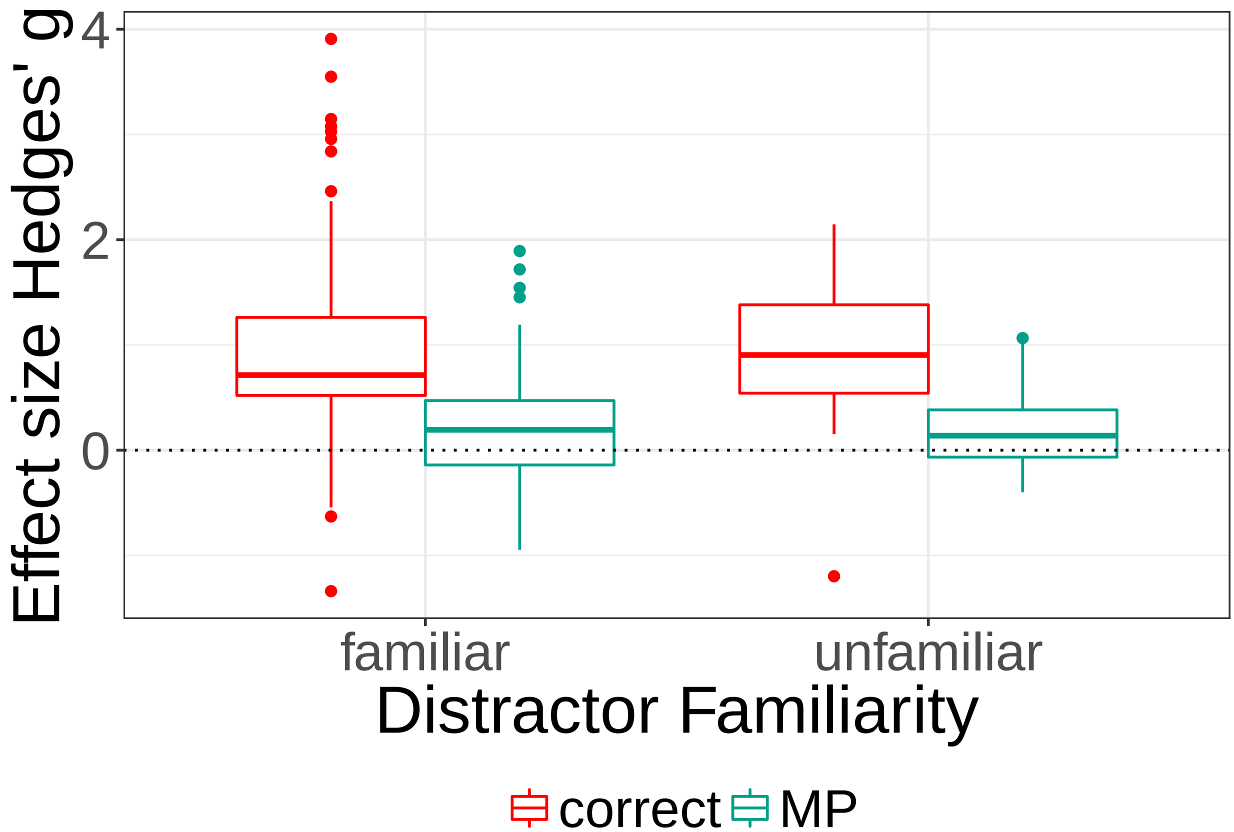
```r
dat$condition_label = ifelse(dat$condition == 1, "correct", "MP")
dat$dist_code <- ifelse(dat$object_pair == "familiar_familiar", "familiar",
    "unfamiliar")

p <- ggplot(dat, aes(mean_age_1/30.44, g_calc, color = condition_label)) + geom_point(aes(size = weights
    shape = dist_code), show.legend = FALSE) + facet_grid(. ~ dist_code) + geom_line(y = 0,
    linetype = "dotted") + geom_smooth(method = "lm", formula = y ~ log(x),
    aes(weight = weights_g)) + scale_color_manual(values = wes_palette(name = "Darjeeling")) +
    theme_bw() + theme(text = element_text(size = 25), legend.title = element_blank(),
    legend.position = "bottom") + xlab("Age in months") + ylab("Effect size Hedges' g")
p
```




```
ggsave("figures/AgeEffect_log_distractor_fam.jpg", p)
```

Plot Distractor Familiarity (w/o age)

```
dat$condition_label = ifelse(dat$condition == 1, "correct", "MP")
dat$dist_code <- ifelse(dat$object_pair == "familiar_familiar", "familiar",
    "unfamiliar")

p <- ggplot(dat, aes(dist_code, g_calc, color = condition_label)) + geom_boxplot() +
    # geom_smooth(method = 'lm', formula = y ~ log(x), aes(weight=weights_g)) +
scale_color_manual(values = wes_palette(name = "Darjeeling")) + theme_bw() +
    theme(text = element_text(size = 25), legend.title = element_blank(), legend.position = "bottom") +
    xlab("Distractor Familiarity") + geom_hline(yintercept = 0, linetype = "dotted") +
    ylab("Effect size Hedges' g")
p
```

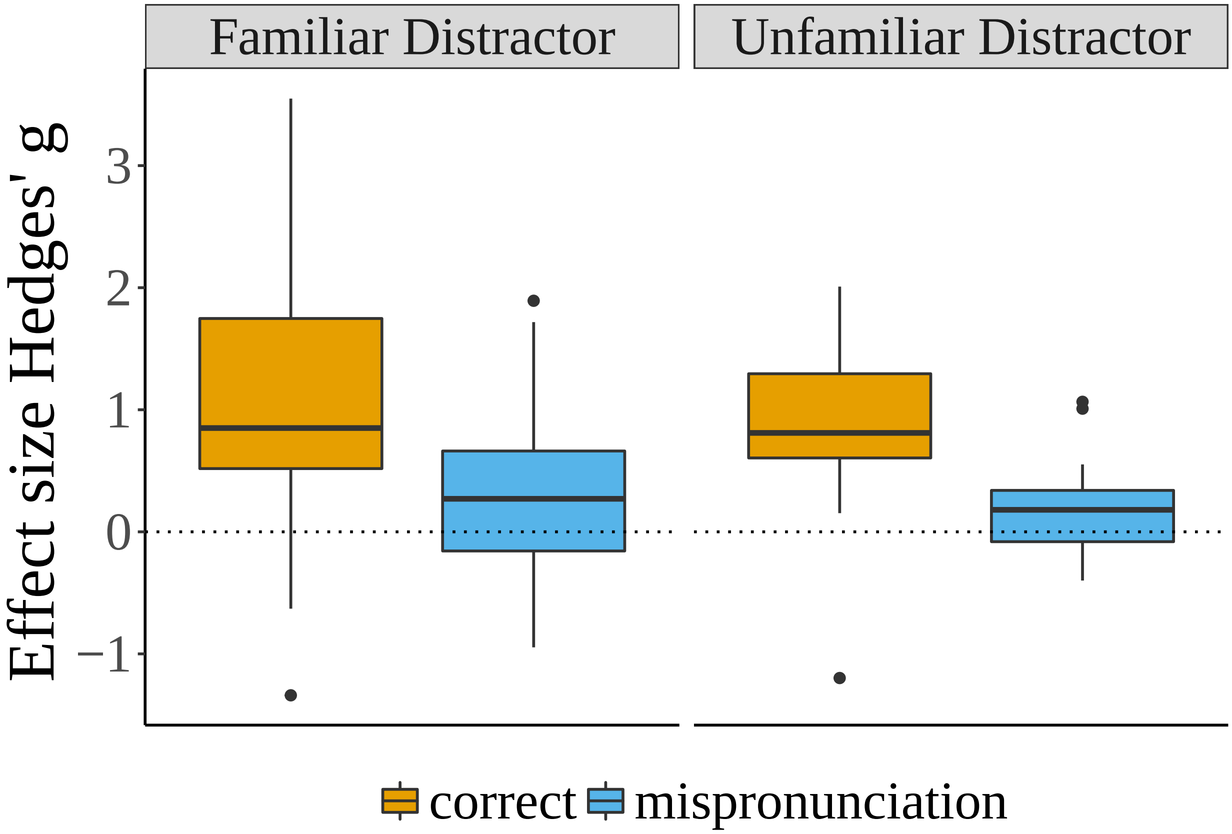



```
ggsave("figures/Distractor_fam_log.jpg", p)
```

Plot Distractor Familiarity (w/o age, subset to age range)

```
mf <- subset(dat, object_pair == "familiar_novel")
min_age <- min(mf$mean_age_1)

mf <- subset(dat, object_pair == "familiar_familiar")
max_age <- max(mf$mean_age_1)

dat_age = dat %>% filter(mean_age_1 > min_age & mean_age_1 < max_age)

dat_age$condition_label = ifelse(dat_age$condition == 1, "correct", "mispronunciation")
dat_age$dist_code <- ifelse(dat_age$object_pair == "familiar_familiar", "Familiar Distractor",
    "Unfamiliar Distractor")

# Color Blind palette:
cbPalette <- c("#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "#D55E00",
    "#CC79A7")

p <- ggplot(dat_age, aes(condition_label, g_calc, fill = condition_label)) +
    geom_boxplot() + facet_grid(. ~ dist_code) + # geom_smooth(method = 'lm', formula = y ~ log(x), aes
scale_fill_manual(values = cbPalette) + apatheme + theme(text = element_text(size = 25),
    legend.title = element_blank(), legend.position = "bottom", axis.title.x = element_blank(),
    axis.text.x = element_blank(), axis.ticks.x = element_blank()) + # xlab('Number of Features Changed
geom_hline(yintercept = 0, linetype = "dotted") + ylab("Effect size Hedges' g")
```

```
p
```

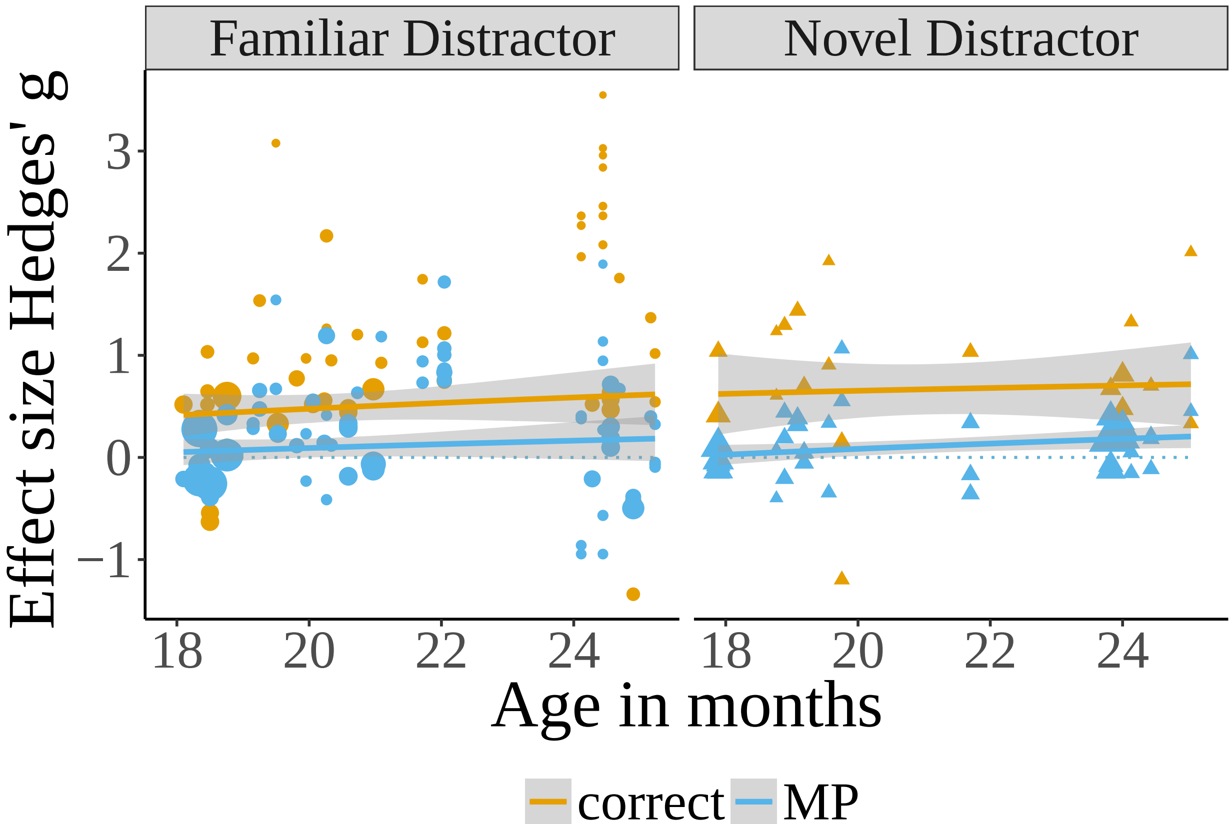



```
ggsave("figures/AgeMatch_Distractor_fam_log.jpg", p)
```

Plot Distractor Familiarity by age subsetted for age

```
mf <- subset(dat, object_pair == "familiar_novel")
min_age <- min(mf$mean_age_1)

mf <- subset(dat, object_pair == "familiar_familiar")
max_age <- max(mf$mean_age_1)

dat_fage = dat %>% filter(mean_age_1 >= min_age & mean_age_1 <= max_age)

dat_fage$dist_fam <- ifelse(dat_fage$object_pair == "familiar_novel", "Novel Distractor",
    "Familiar Distractor")

# Color Blind palette:
cbPalette <- c("#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "#D55E00",
    "#CC79A7")

p <- ggplot(dat_fage, aes(mean_age_1/30.44, g_calc, color = condition_label)) +
    geom_point(aes(size = weights_g, shape = dist_fam), show.legend = FALSE) +
    facet_grid(. ~ dist_fam) + scale_colour_manual(values = cbPalette) + geom_line(y = 0,
    linetype = "dotted") + geom_smooth(method = "lm", formula = y ~ log(x),
```

```r
    aes(weight = weights_g)) + apatheme + theme(legend.title = element_blank(),
    legend.position = "bottom") + xlab("Age in months") + ylab("Effect size Hedges' g")
p
```




```r
ggsave("figures/AgeEffect_log_DistFam_agesub.jpg", p)
```

Position of Mispronunciation (onset, medial)

```r
# table(db_ET_MP$mispron_location)

db_ET_MP1 = db_ET_MP %>% filter(mispron_location == "onset" | mispron_location ==
    "medial")

# rma_NFeatures <- rma.mv(g_calc, g_var_calc, mods = ~as.ordered(n_feature),
# data = db_ET_MP, random = ~collapse | short_cite)
rma_Location <- rma.mv(g_calc, g_var_calc, mods = ~mispron_location, data = db_ET_MP1,
    random = ~collapse | short_cite)


summary(rma_Location)
```

```
##
## Multivariate Meta-Analysis Model (k = 114; method: REML)
##
##    logLik  Deviance       AIC       BIC      AICc
## -57.5043  115.0085  123.0085  133.8825  123.3823
```

```
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 24)
## inner factor: collapse   (nlvls = 41)
##
##             estim    sqrt  fixed
## tau^2      0.1502  0.3876     no
## rho        0.5421             no
##
## Test for Residual Heterogeneity:
## QE(df = 112) = 392.6421, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0419, p-val = 0.8378
##
## Model Results:
##
##                          estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                    0.2306  0.0852  2.7063  0.0068   0.0636  0.3977
## mispron_locationmedial     0.0307  0.1498  0.2048  0.8378  -0.2629  0.3243
##
## intrcpt                  **
## mispron_locationmedial
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Position of Mispronunciation with age moderator

```
# table(db_ET_MP$mispron_location)

db_ET_MP1 = db_ET_MP %>% filter(mispron_location == "onset" | mispron_location ==
    "medial")


rma_LocationAge <- rma.mv(g_calc, g_var_calc, mods = ~mispron_location * age.C,
    data = db_ET_MP1, random = ~collapse | short_cite)


summary(rma_LocationAge)
```

```
##
## Multivariate Meta-Analysis Model (k = 114; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -56.0484  112.0967  124.0967  140.2996  124.9122
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 24)
## inner factor: collapse   (nlvls = 41)
##
```

```
##              estim    sqrt  fixed
## tau^2       0.1563  0.3953     no
## rho         0.5238             no
##
## Test for Residual Heterogeneity:
## QE(df = 110) = 386.0990, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## QM(df = 3) = 1.2243, p-val = 0.7472
##
## Model Results:
##
##                               estimate      se    zval    pval    ci.lb
## intrcpt                         0.2296  0.0872  2.6339  0.0084   0.0588
## mispron_locationmedial          0.0832  0.1684  0.4937  0.6215  -0.2470
## age.C                           0.0117  0.0179  0.6531  0.5137  -0.0234
## mispron_locationmedial:age.C    0.0179  0.0337  0.5305  0.5958  -0.0482
##                                ci.ub
## intrcpt                       0.4005  **
## mispron_locationmedial        0.4133
## age.C                         0.0469
## mispron_locationmedial:age.C  0.0840
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Position of Mispronunciation with condition moderator

```
# table(db_ET_MP$mispron_location)

db_ET_MPl = db_ET_MP %>% filter(mispron_location == "onset" | mispron_location ==
    "medial")


rma_LocationCondition <- rma.mv(g_calc, g_var_calc, mods = ~mispron_location *
    condition, data = db_ET_MPl, random = ~collapse | short_cite)


summary(rma_LocationCondition)
```

```
##
## Multivariate Meta-Analysis Model (k = 114; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -57.5043  115.0085  123.0085  133.8825  123.3823
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 24)
## inner factor: collapse   (nlvls = 41)
##
##              estim    sqrt  fixed
## tau^2       0.1502  0.3876     no
```

```
## rho        0.5421             no
##
## Test for Residual Heterogeneity:
## QE(df = 112) = 392.6421, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0419, p-val = 0.8378
##
## Model Results:
##
##                          estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt                    0.2306  0.0852  2.7063  0.0068   0.0636  0.3977
## mispron_locationmedial     0.0307  0.1498  0.2048  0.8378  -0.2629  0.3243
##
## intrcpt                  **
## mispron_locationmedial
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Position of Mispronunciation with age and condition moderators

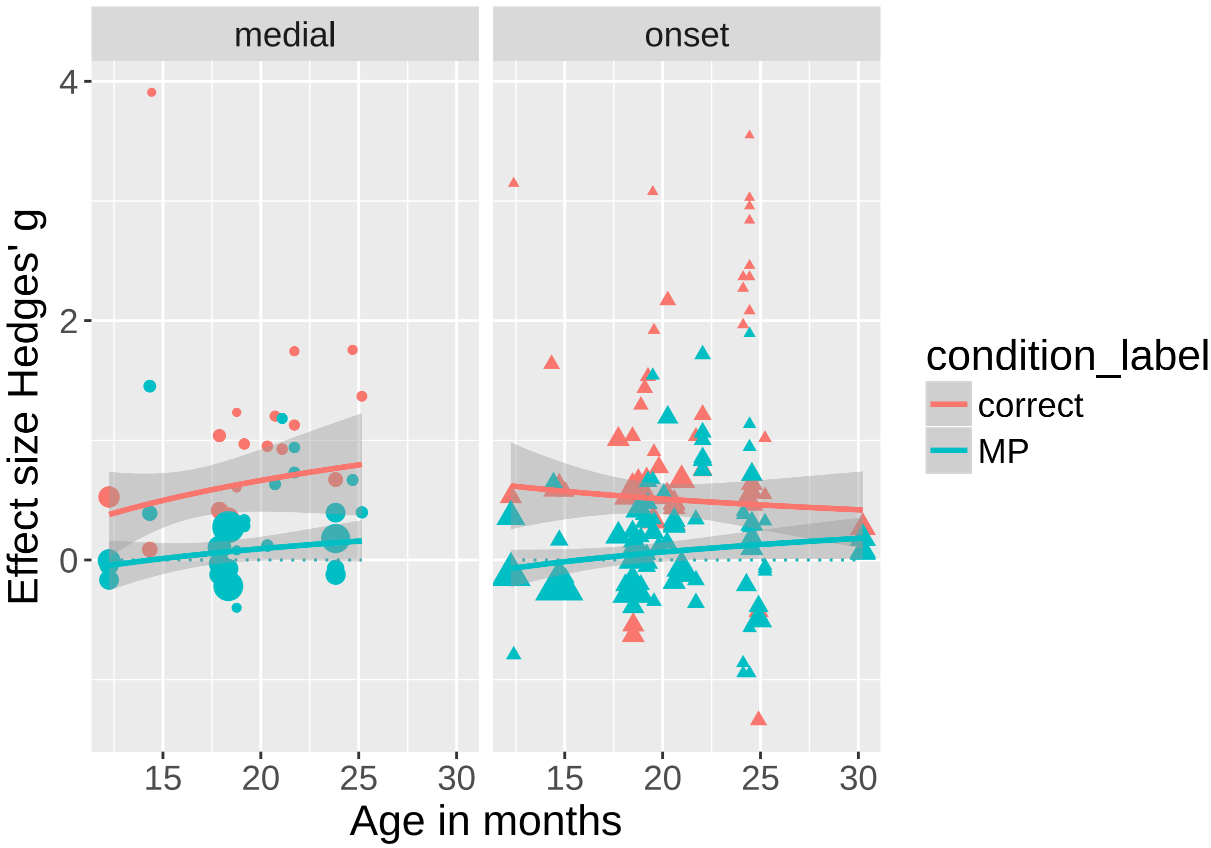
```
# table(db_ET_MP$mispron_location)

db_ET_MPl = db_ET_MP %>% filter(mispron_location == "onset" | mispron_location ==
    "medial")


rma_LocationCondition <- rma.mv(g_calc, g_var_calc, mods = ~mispron_location *
    condition * age.C, data = db_ET_MPl, random = ~collapse | short_cite)


summary(rma_LocationCondition)
```

```
##
## Multivariate Meta-Analysis Model (k = 114; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -56.0484  112.0967  124.0967  140.2996  124.9122
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 24)
## inner factor: collapse   (nlvls = 41)
##
##             estim    sqrt  fixed
## tau^2      0.1563  0.3953     no
## rho        0.5238             no
##
## Test for Residual Heterogeneity:
## QE(df = 110) = 386.0990, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
```

```
## QM(df = 3) = 1.2243, p-val = 0.7472
##
## Model Results:
##
##                                estimate      se    zval    pval    ci.lb
## intrcpt                          0.2296  0.0872  2.6339  0.0084   0.0588
## mispron_locationmedial           0.0832  0.1684  0.4937  0.6215  -0.2470
## age.C                            0.0117  0.0179  0.6531  0.5137  -0.0234
## mispron_locationmedial:age.C     0.0179  0.0337  0.5305  0.5958  -0.0482
##                                 ci.ub
## intrcpt                        0.4005  **
## mispron_locationmedial         0.4133
## age.C                          0.0469
## mispron_locationmedial:age.C   0.0840
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting Position of Mispronunciation

```
# dat.p <- subset(dat, mispron_location == 'onset' | mispron_location ==
# 'medial' | mispron_location == 'offset')

dat.p <- subset(dat, mispron_location == "onset" | mispron_location == "medial")

p <- ggplot(dat.p, aes(mean_age_1/30.44, g_calc, color = condition_label)) +
    geom_point(aes(size = weights_g, shape = mispron_location), show.legend = FALSE) +
    facet_grid(. ~ mispron_location) + geom_line(y = 0, linetype = "dotted") +
    geom_smooth(method = "lm", formula = y ~ log(x), aes(weight = weights_g)) +
    theme(text = element_text(size = 16)) + xlab("Age in months") + ylab("Effect size Hedges' g")
p
```




```
ggsave("figures/AgeEffect_log_position.jpg", p)
```

Distractor Overlap

```
rma_DistractorOverlap <- rma.mv(g_calc, g_var_calc, mods = ~distractor_overlap,
    data = db_ET_MP, random = ~collapse | short_cite)

summary(rma_DistractorOverlap)
```

```
##
## Multivariate Meta-Analysis Model (k = 147; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -67.3747  134.7494  148.7494  169.4402  149.5852
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1271  0.3565     no
## rho        0.6003             no
##
## Test for Residual Heterogeneity:
## QE(df = 142) = 459.3146, p-val < .0001
```

```
##
## Test of Moderators (coefficient(s) 2,3,4,5):
## QM(df = 4) = 1.9399, p-val = 0.7468
##
## Model Results:
##
##                                 estimate      se    zval    pval    ci.lb
## intrcpt                           0.0868  0.3928  0.2209  0.8252  -0.6831
## distractor_overlapno              0.2610  0.4051  0.6444  0.5193  -0.5329
## distractor_overlapnovel           0.0609  0.4102  0.1485  0.8819  -0.7430
## distractor_overlaponset           0.1245  0.3950  0.3151  0.7527  -0.6498
## distractor_overlaponset/medial    0.2192  0.5461  0.4013  0.6882  -0.8513
##                                  ci.ub
## intrcpt                         0.8566
## distractor_overlapno            1.0549
## distractor_overlapnovel         0.8648
## distractor_overlaponset         0.8987
## distractor_overlaponset/medial  1.2896
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Overlap with age moderator

```r
rma_DistractorOverlap <- rma.mv(g_calc, g_var_calc, mods = ~age.C * distractor_overlap,
    data = db_ET_MP, random = ~collapse | short_cite)

summary(rma_DistractorOverlap)
```

```
##
## Multivariate Meta-Analysis Model (k = 147; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -63.8569  127.7138  147.7138  177.0586  149.4326
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1272  0.3567     no
## rho        0.5803             no
##
## Test for Residual Heterogeneity:
## QE(df = 139) = 426.8044, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8):
## QM(df = 7) = 6.1553, p-val = 0.5217
##
## Model Results:
##
##                                 estimate      se     zval    pval    ci.lb
```

```
## intrcpt                          0.0983  0.3957   0.2483  0.8039  -0.6772
## age.C                            0.0174  0.0214   0.8130  0.4162  -0.0246
## distractor_overlapno             0.3432  0.4126   0.8319  0.4055  -0.4654
## distractor_overlapnovel         -0.0319  0.4197  -0.0759  0.9395  -0.8544
## distractor_overlaponset          0.1267  0.3979   0.3184  0.7502  -0.6532
## distractor_overlaponset/medial   0.1484  0.5553   0.2672  0.7893  -0.9399
## age.C:distractor_overlapno       0.0132  0.0297   0.4431  0.6577  -0.0451
## age.C:distractor_overlapnovel    0.0142  0.0342   0.4142  0.6787  -0.0529
##                                 ci.ub
## intrcpt                        0.8737
## age.C                          0.0594
## distractor_overlapno           1.1518
## distractor_overlapnovel        0.7907
## distractor_overlaponset        0.9066
## distractor_overlaponset/medial  1.2367
## age.C:distractor_overlapno     0.0714
## age.C:distractor_overlapnovel  0.0812
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Overlap with condition moderator

```
rma_DistractorOverlap <- rma.mv(g_calc, g_var_calc, mods = ~condition * distractor_overlap,
    data = db_ET_MP, random = ~collapse | short_cite)

summary(rma_DistractorOverlap)
```

```
##
## Multivariate Meta-Analysis Model (k = 147; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -67.3747  134.7494  148.7494  169.4402  149.5852
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1271  0.3565     no
## rho        0.6003             no
##
## Test for Residual Heterogeneity:
## QE(df = 142) = 459.3146, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5):
## QM(df = 4) = 1.9399, p-val = 0.7468
##
## Model Results:
##
##                                 estimate      se    zval    pval    ci.lb
## intrcpt                           0.0868  0.3928  0.2209  0.8252  -0.6831
```

```
## distractor_overlapno              0.2610  0.4051  0.6444  0.5193  -0.5329
## distractor_overlapnovel           0.0609  0.4102  0.1485  0.8819  -0.7430
## distractor_overlaponset           0.1245  0.3950  0.3151  0.7527  -0.6498
## distractor_overlaponset/medial    0.2192  0.5461  0.4013  0.6882  -0.8513
##                                  ci.ub
## intrcpt                         0.8566
## distractor_overlapno            1.0549
## distractor_overlapnovel         0.8648
## distractor_overlaponset         0.8987
## distractor_overlaponset/medial  1.2896
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Distractor Overlap with age and condition moderators

```r
rma_DistractorOverlap <- rma.mv(g_calc, g_var_calc, mods = ~age.C * condition *
    distractor_overlap, data = db_ET_MP, random = ~collapse | short_cite)

summary(rma_DistractorOverlap)
```

```
##
## Multivariate Meta-Analysis Model (k = 147; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -63.8569  127.7138  147.7138  177.0586  149.4326
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1272  0.3567     no
## rho        0.5803             no
##
## Test for Residual Heterogeneity:
## QE(df = 139) = 426.8044, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8):
## QM(df = 7) = 6.1553, p-val = 0.5217
##
## Model Results:
##
##                                 estimate      se     zval    pval    ci.lb
## intrcpt                           0.0983  0.3957   0.2483  0.8039  -0.6772
## age.C                             0.0174  0.0214   0.8130  0.4162  -0.0246
## distractor_overlapno              0.3432  0.4126   0.8319  0.4055  -0.4654
## distractor_overlapnovel          -0.0319  0.4197  -0.0759  0.9395  -0.8544
## distractor_overlaponset           0.1267  0.3979   0.3184  0.7502  -0.6532
## distractor_overlaponset/medial    0.1484  0.5553   0.2672  0.7893  -0.9399
## age.C:distractor_overlapno        0.0132  0.0297   0.4431  0.6577  -0.0451
## age.C:distractor_overlapnovel     0.0142  0.0342   0.4142  0.6787  -0.0529
```

```
##                                    ci.ub
## intrcpt                           0.8737
## age.C                             0.0594
## distractor_overlapno              1.1518
## distractor_overlapnovel           0.7907
## distractor_overlaponset           0.9066
## distractor_overlaponset/medial    1.2367
## age.C:distractor_overlapno        0.0714
## age.C:distractor_overlapnovel     0.0812
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting Distractor Overlap

```
p <- ggplot(dat, aes(mean_age_1/30.44, g_calc, color = condition_label)) + geom_point(aes(size = weights
    shape = distractor_overlap), show.legend = FALSE) + facet_grid(. ~ distractor_overlap) +
    geom_line(y = 0, linetype = "dotted") + geom_smooth(method = "lm", formula = y ~
    log(x), aes(weight = weights_g)) + theme(text = element_text(size = 16)) +
    xlab("Age in months") + ylab("Effect size Hedges' g")
p
```


```
ggsave("figures/AgeEffect_log_distractor_overlap.jpg", p)
```

Language effect

```r
dat$condition_label = ifelse(dat$condition == 1, "Correct", "Misp")

dat$lang_family = ifelse(dat$native_lang == "American English" | dat$native_lang ==
    "British English" | dat$native_lang == "Dutch" | dat$native_lang == "English" |
    dat$native_lang == "Danish" | dat$native_lang == "Swedish" | dat$native_lang ==
    "German", "Germanic", ifelse(dat$native_lang == "French" | dat$native_lang ==
    "Catalan" | dat$native_lang == "Spanish" | dat$native_lang == "Catalan-Spanish" |
    dat$native_lang == "Swiss French", "Romanic", "Sino-Tibetian"))

rma_lang_interaction <- rma.mv(g_calc, g_var_calc, mods = ~lang_family, data = dat,
    random = ~collapse | short_cite)
summary(rma_lang_interaction)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -356.7240   713.4480   723.4480   741.0151   723.6959
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1291  0.3593     no
## rho        0.6903             no
##
## Test for Residual Heterogeneity:
## QE(df = 248) = 1273.5943, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3):
## QM(df = 2) = 4.6882, p-val = 0.0959
##
## Model Results:
##
##                             estimate      se     zval    pval    ci.lb
## intrcpt                       0.4313  0.0680   6.3464  <.0001   0.2981
## lang_familyRomanic            0.3308  0.1670   1.9805  0.0476   0.0034
## lang_familySino-Tibetian     -0.1382  0.2034  -0.6793  0.4970  -0.5369
##                              ci.ub
## intrcpt                     0.5645  ***
## lang_familyRomanic          0.6582    *
## lang_familySino-Tibetian    0.2605
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Language effect with age moderator

```
dat$condition_label = ifelse(dat$condition == 1, "Correct", "Misp")

dat$lang_family = ifelse(dat$native_lang == "American English" | dat$native_lang ==
    "British English" | dat$native_lang == "Dutch" | dat$native_lang == "English" |
    dat$native_lang == "Danish" | dat$native_lang == "Swedish" | dat$native_lang ==
    "German", "Germanic", ifelse(dat$native_lang == "French" | dat$native_lang ==
    "Catalan" | dat$native_lang == "Spanish" | dat$native_lang == "Catalan-Spanish" |
    dat$native_lang == "Swiss French", "Romanic", "Sino-Tibetian"))

rma_lang_interaction <- rma.mv(g_calc, g_var_calc, mods = ~age.C * lang_family,
    data = dat, random = ~collapse | short_cite)
summary(rma_lang_interaction)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -352.2890   704.5780   720.5780   748.5880   721.1881
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1382  0.3717     no
## rho        0.7726             no
##
## Test for Residual Heterogeneity:
## QE(df = 245) = 1249.7278, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 9.3777, p-val = 0.0949
##
## Model Results:
##
##                                  estimate      se     zval    pval    ci.lb
## intrcpt                            0.4475  0.0717   6.2378  <.0001   0.3069
## age.C                              0.0105  0.0119   0.8803  0.3787  -0.0129
## lang_familyRomanic                 0.3390  0.1725   1.9652  0.0494   0.0009
## lang_familySino-Tibetian          -0.1789  0.2463  -0.7264  0.4676  -0.6615
## age.C:lang_familyRomanic           0.0562  0.0328   1.7147  0.0864  -0.0080
## age.C:lang_familySino-Tibetian    -0.0153  0.0444  -0.3453  0.7299  -0.1024
##                                   ci.ub
## intrcpt                          0.5882  ***
## age.C                            0.0338
## lang_familyRomanic               0.6770    *
## lang_familySino-Tibetian         0.3038
## age.C:lang_familyRomanic         0.1205    .
## age.C:lang_familySino-Tibetian   0.0717
##
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Language effect with condition moderator

```r
dat$condition_label = ifelse(dat$condition == 1, "Correct", "Misp")

dat$lang_family = ifelse(dat$native_lang == "American English" | dat$native_lang ==
    "British English" | dat$native_lang == "Dutch" | dat$native_lang == "English" |
    dat$native_lang == "Danish" | dat$native_lang == "Swedish" | dat$native_lang ==
    "German", "Germanic", ifelse(dat$native_lang == "French" | dat$native_lang ==
    "Catalan" | dat$native_lang == "Spanish" | dat$native_lang == "Catalan-Spanish" |
    dat$native_lang == "Swiss French", "Romanic", "Sino-Tibetian"))

rma_lang_interaction <- rma.mv(g_calc, g_var_calc, mods = ~condition * lang_family,
    data = dat, random = ~collapse | short_cite)
summary(rma_lang_interaction)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -249.3297   498.6593   514.6593   542.6694   515.2695
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1287  0.3588     no
## rho        0.6904             no
##
## Test for Residual Heterogeneity:
## QE(df = 245) = 1027.2297, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 221.2361, p-val < .0001
##
## Model Results:
##
##                                    estimate      se     zval    pval
## intrcpt                              0.2675  0.0691   3.8723  0.0001
## condition                            0.4775  0.0360  13.2740  <.0001
## lang_familyRomanic                   0.2014  0.1782   1.1303  0.2584
## lang_familySino-Tibetian            -0.2804  0.2176  -1.2883  0.1976
## condition:lang_familyRomanic         0.0919  0.1238   0.7423  0.4579
## condition:lang_familySino-Tibetian   0.2343  0.1757   1.3338  0.1823
##                                      ci.lb   ci.ub
## intrcpt                             0.1321  0.4029  ***
## condition                           0.4070  0.5480  ***
## lang_familyRomanic                 -0.1479  0.5507
## lang_familySino-Tibetian           -0.7069  0.1462
## condition:lang_familyRomanic       -0.1508  0.3346
```

```
## condition:lang_familySino-Tibetian  -0.1100  0.5787
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Language effect with age and condition moderators

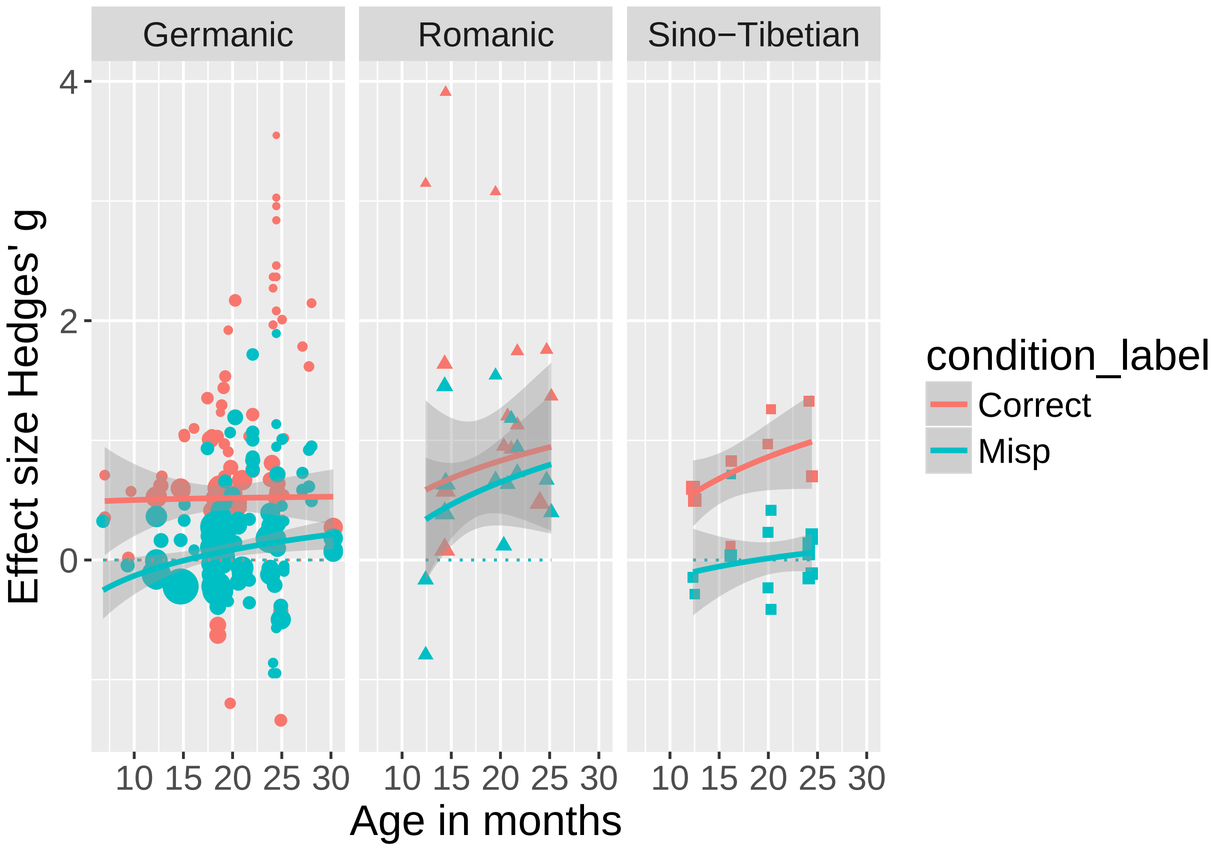
```
dat$condition_label = ifelse(dat$condition == 1, "Correct", "Misp")

dat$lang_family = ifelse(dat$native_lang == "American English" | dat$native_lang ==
    "British English" | dat$native_lang == "Dutch" | dat$native_lang == "English" |
    dat$native_lang == "Danish" | dat$native_lang == "Swedish" | dat$native_lang ==
    "German", "Germanic", ifelse(dat$native_lang == "French" | dat$native_lang ==
    "Catalan" | dat$native_lang == "Spanish" | dat$native_lang == "Catalan-Spanish" |
    dat$native_lang == "Swiss French", "Romanic", "Sino-Tibetian"))

rma_lang_interaction <- rma.mv(g_calc, g_var_calc, mods = ~age.C * condition *
    lang_family, data = dat, random = ~collapse | short_cite)
summary(rma_lang_interaction)
```

```
##
## Multivariate Meta-Analysis Model (k = 251; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -245.9822   491.9645   519.9645   568.6350   521.8395
##
## Variance Components:
##
## outer factor: short_cite (nlvls = 32)
## inner factor: collapse   (nlvls = 52)
##
##             estim    sqrt  fixed
## tau^2      0.1334  0.3653     no
## rho        0.7359             no
##
## Test for Residual Heterogeneity:
## QE(df = 239) = 998.1810, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6,7,8,9,10,11,12):
## QM(df = 11) = 225.6133, p-val < .0001
##
## Model Results:
##
##                                          estimate      se     zval
## intrcpt                                    0.2813  0.0713   3.9440
## age.C                                      0.0124  0.0124   1.0028
## condition                                  0.4795  0.0365  13.1408
## lang_familyRomanic                         0.2318  0.1881   1.2323
## lang_familySino-Tibetian                  -0.2461  0.2491  -0.9879
## age.C:condition                            0.0024  0.0082   0.2884
## age.C:lang_familyRomanic                   0.0419  0.0352   1.1900
## age.C:lang_familySino-Tibetian            -0.0012  0.0461  -0.0264
## condition:lang_familyRomanic               0.0558  0.1366   0.4083
```

```
## condition:lang_familySino-Tibetian          0.2910  0.1877   1.5506
## age.C:condition:lang_familyRomanic         -0.0116  0.0295  -0.3940
## age.C:condition:lang_familySino-Tibetian    0.0215  0.0336   0.6405
##                                             pval    ci.lb   ci.ub
## intrcpt                                   <.0001   0.1415  0.4210  ***
## age.C                                     0.3159  -0.0118  0.0367
## condition                                 <.0001   0.4080  0.5510  ***
## lang_familyRomanic                        0.2178  -0.1369  0.6004
## lang_familySino-Tibetian                  0.3232  -0.7343  0.2421
## age.C:condition                           0.7730  -0.0137  0.0184
## age.C:lang_familyRomanic                  0.2341  -0.0271  0.1108
## age.C:lang_familySino-Tibetian            0.9790  -0.0915  0.0891
## condition:lang_familyRomanic              0.6831  -0.2120  0.3236
## condition:lang_familySino-Tibetian        0.1210  -0.0768  0.6588
## age.C:condition:lang_familyRomanic        0.6935  -0.0694  0.0462
## age.C:condition:lang_familySino-Tibetian  0.5219  -0.0443  0.0874
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting Language Effect

```
dat$lang_family = ifelse(dat$native_lang == "American English" | dat$native_lang ==
    "British English" | dat$native_lang == "Dutch" | dat$native_lang == "English" |
    dat$native_lang == "German", "Germanic", ifelse(dat$native_lang == "French" |
    dat$native_lang == "Catalan" | dat$native_lang == "Spanish" | dat$native_lang ==
    "Catalan-Spanish" | dat$native_lang == "Swiss French", "Romanic", "Sino-Tibetian"))

p <- ggplot(dat, aes(mean_age_1/30.44, g_calc, color = condition_label)) + geom_point(aes(size = weights
    shape = lang_family), show.legend = FALSE) + facet_grid(. ~ lang_family) +
    geom_line(y = 0, linetype = "dotted") + geom_smooth(method = "lm", formula = y ~
    log(x), aes(weight = weights_g)) + theme(text = element_text(size = 16)) +
    xlab("Age in months") + ylab("Effect size Hedges' g")
p
```




```
ggsave("figures/AgeEffect_log_language.jpg", p)
```