pilot1

Samah

2023-03-14

uncomment below to render to html

output:

bookdown::html_document2:

toc: true

toc_depth: 4

theme: cosmo

highlight: tango

uncomment below to render to pdf

output: bookdown::pdf_book: toc: true toc_depth: 4 highlight: tango

bibliography: [references/packages.bib, references/references.bib] biblio-style: apalike nocite: '@*' —

Results

```
# additional libraries
library("knitr")
library("janitor")
library("broom.mixed")
library("lme4")
library("emmeans")
library("tidyverse")
library("kableExtra")
```

```
## Warning in !is.null(rmarkdown::metadata$output) && rmarkdown::metadata$output
## %in% : 'length(x) = 2 > 1' in coercion to 'logical(1)'
```

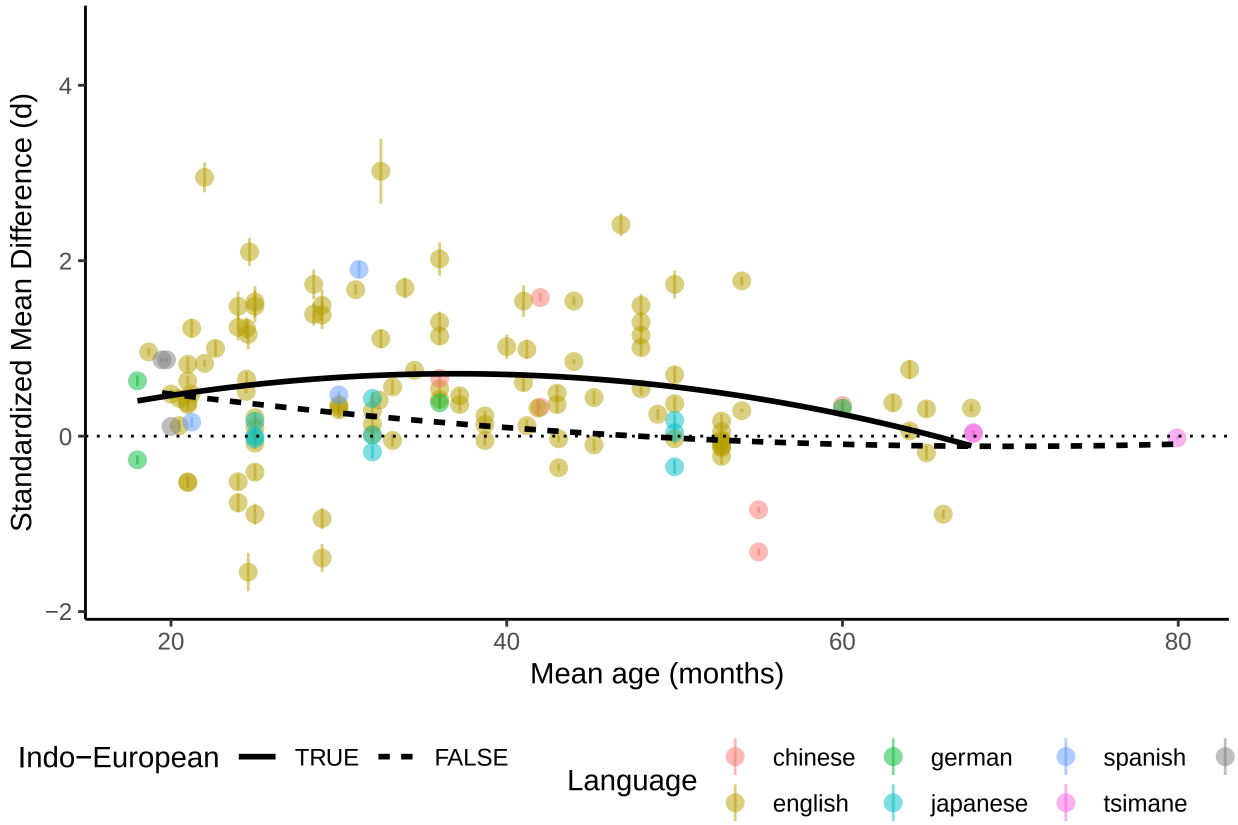
```r
library("modelr")
library("broom")
library("nlme")
library("meta")
library("metafor")
library(jtools) # Load jtools
theme_set(theme_classic())
```

```r
# reading the data file
pilot1_data = read_csv("252.csv")
df_shape= filter(pilot1_data, !is.na(d))
# pilot1_data = pilot1_data %>%
#   select(ID, Title, d, d_var, Author)

df_shape_summary = df_shape %>%
  group_by(ID, Title, Author) %>%
  summarize(mean = mean(d),
            mean_se = mean(d_var))
```

First, Visualizing the data to have an initial idea of how it looks. First dividing the language group into two groups: the first one is the indo-european group which includes the English and the Spanish languages. The second group includes the rest of the languages: Japanese, Chinese, Tsimane.

```r
df_shape$indoeuropean <- fct_relevel(as.factor(df_shape$language %in%
                                          c("english","spanish", "german")),
                                         "TRUE")

# creating a plot that shows the effects sizes colored per language group as well as the polynomial reg

ggplot(df_shape,
       aes(x = mean_age_months, y = d, color = language))+
  geom_pointrange(aes(ymin = d - d_var, ymax = d + d_var),
                  alpha = .5) +
  geom_smooth(aes(group = indoeuropean,
                  lty  = indoeuropean),
              col = "black",
              method = "lm", se = FALSE,
              formula = y ~ poly(x,2)) +
  geom_hline(yintercept = 0, lty = 3) +
  ylab("Standardized Mean Difference (d)") +
  xlab("Mean age (months)") +
  scale_color_discrete(name = "Language") +
  scale_linetype_discrete(name = "Indo-European") +
  theme(legend.position = "bottom")
```

```
## Warning: Removed 8 rows containing non-finite values (‘stat_smooth()‘).

## Warning: Removed 8 rows containing missing values (‘geom_pointrange()‘).
```




```
ggsave("first graph.png", width = 7, height = 4)
```

```
## Warning: Removed 8 rows containing non-finite values (`stat_smooth()`).
## Removed 8 rows containing missing values (`geom_pointrange()`).
```

using the meta-analytic function meta-gen which calculates the weights for each effects and confidence interval, pooled effect size, the heterogeneity.

```
m.gen <- metagen( TE= d,
                  seTE = d_var,
                  studlab = ID,
                  data = df_shape,
                  sm = "SMD",
                  fixed = FALSE,
                  random = TRUE,
                  method.tau = "REML",
                  hakn = TRUE,
                  title = "pilot shape bias meta-analysis"

)

summary(m.gen)['TE']
```

```
## $TE
```

```
##   [1]  0.32  0.03 -0.02  0.04  0.33 -0.84  1.58 -1.32  1.54  1.77  0.85  0.29
##  [13]  1.54  0.76  0.61  0.06  0.33  0.36  0.31  0.36  0.49 -0.19  0.30  1.02
##  [25]  0.38 -0.05  0.36  0.12 -0.10  0.12  0.65  1.39  1.11  0.56  0.46  0.99
##  [37]  0.44  0.43  1.23  1.73  3.02  0.05 -0.06  0.17 -0.04 -0.23 -0.09 -0.13
##  [49] -0.12 -0.36 -0.03  0.32  2.41 -0.89  0.51  0.96  0.41  1.90 -0.52  0.38
##  [61] -0.53  0.82  0.63  0.36  0.21  0.29  0.70  0.10  0.14  0.37 -0.08  0.02
##  [73] -0.03  0.17  0.43  0.18  0.00  0.01  0.04 -0.03 -0.18 -0.35  1.48 -0.89
##  [85]  1.53 -0.41  1.48 -0.52  1.24 -0.76  1.49 -0.94  1.38 -1.39  0.75  1.69
##  [97]  2.10  0.87  0.87  0.11  0.63 -0.27  1.23  0.16  2.95  0.83  0.54  1.01
## [109]  1.14  1.15  2.02  1.30  1.30  1.49  0.42  0.54  1.73  0.25  0.13  0.23
## [121] -0.05  0.48  0.48  1.00  0.66  0.38  0.35  0.32  1.16 -1.55  1.67  0.47
## [133]  1.81  4.02  2.06  1.56  1.42  1.38  0.73  0.34
```

```
m.gen["TE.fixed"]
```

```
## $TE.fixed
## [1] 0.317156
```

```
m.gen["TE.random"]
```

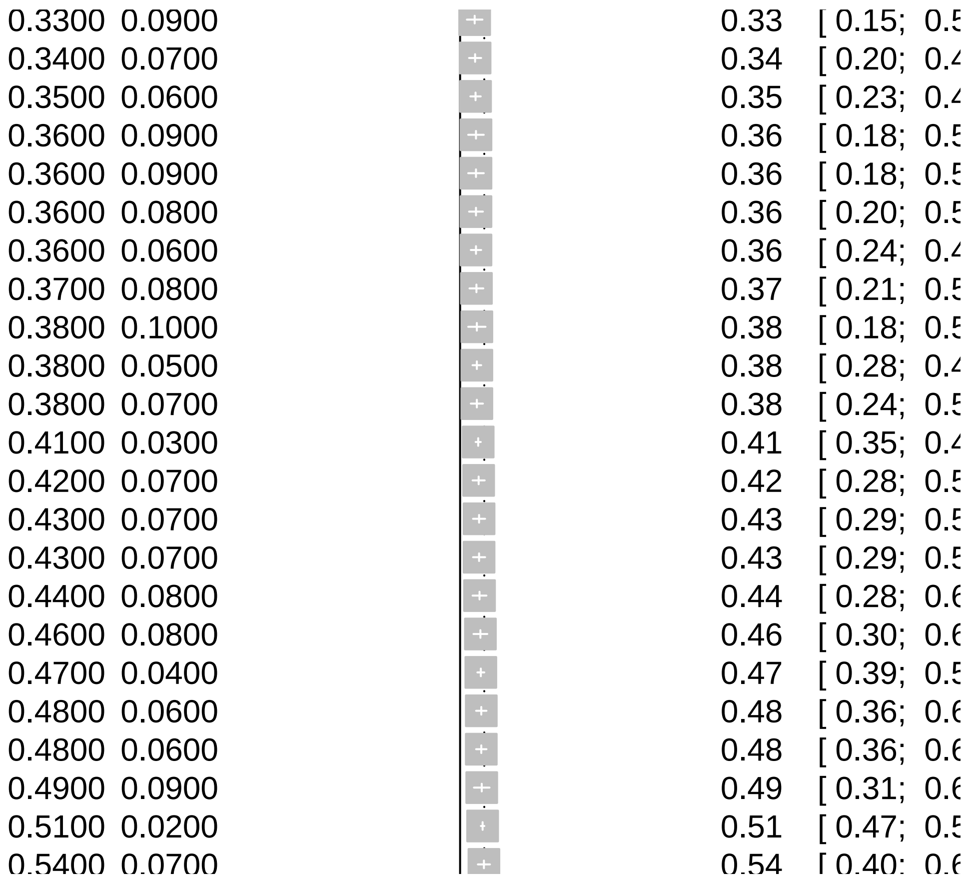
```
## $TE.random
## [1] 0.5474713
```

```
m.gen["w.random"]
```

```
## $w.random
##   [1] 1.536920 1.538575 1.539759 1.538575 1.539759 1.538575 1.534797 1.536920
##   [9] 1.534797 1.534797 1.538575 1.539759 1.467455 1.512511 1.517331 1.525665
##  [17] 1.521718 1.521718 1.521718 1.521718 1.521718 1.525665 1.521718 1.495546
##  [25] 1.517331 1.529164 1.525665 1.529164 1.529164 1.529164 1.525665 1.501610
##  [33] 1.512511 1.525665 1.525665 1.512511 1.525665 1.529164 1.507268 1.475031
##  [41] 1.272342 1.525665 1.525665 1.525665 1.525665 1.521718 1.525665 1.525665
##  [49] 1.525665 1.536920 1.536920 1.521718 1.501610 1.534797 1.539759 1.536920
##  [57] 1.538575 1.521718 1.529164 1.534797 1.532210 1.525665 1.534797 1.532210
##  [65] 1.529164 1.529164 1.521718 1.529164 1.529164 1.525665 1.529164 1.529164
##  [73] 1.529164 1.529164 1.529164 1.529164 1.529164 1.529164 1.529164 1.529164
##  [81] 1.529164 1.525665 1.467455 1.507268 1.467455 1.521718 1.475031 1.521718
##  [89] 1.489088 1.512511 1.467455 1.507268 1.482245 1.482245 1.529164 1.507268
##  [97] 1.482245 1.539759 1.539759 1.540471 1.532210 1.534797 1.512511 1.532210
## [105] 1.475031 1.536920 1.529164 1.521718 1.517331 1.517331 1.459530 1.507268
## [113] 1.507268 1.501610 1.529164 1.529164 1.482245 1.532210 1.532210 1.532210
## [121] 1.532210 1.532210 1.532210 1.521718 1.529164 1.529164 1.532210 1.529164
## [129] 1.475031 1.433790 1.532210 1.536920 1.482245 1.026745 1.451269 1.495546
## [137] 1.501610 1.507268 1.525665 1.529164
```

forest plot using the m-gen function object

```
forextobj <- forest.meta(m.gen,
             sortvar = TE,
             prediction = TRUE,
             print.tau2 = FALSE,
             leftlabs = c("Author", "g", "SE"))
```

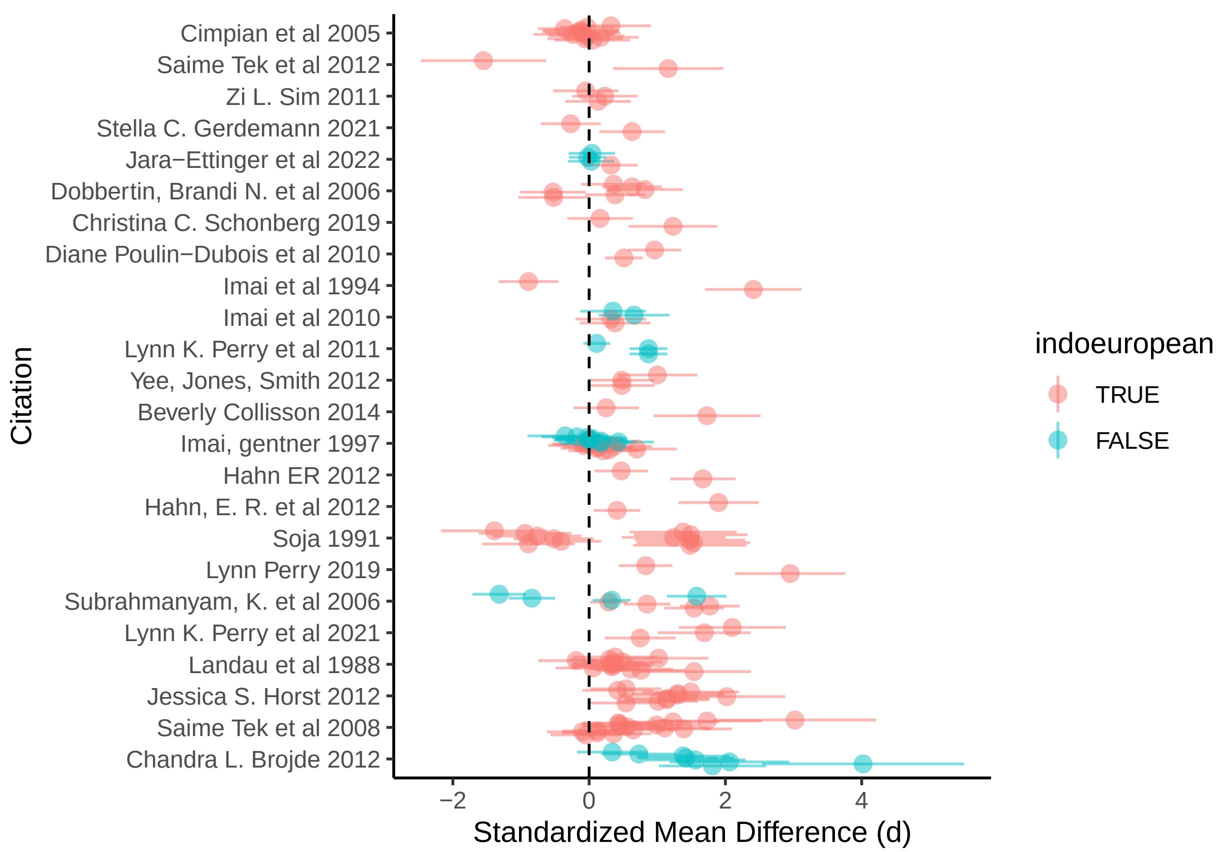


forest plot from the rma model:

```
forest(mod)
forest_data <-tibble(yi = mod$yi,
                     se = sqrt(mod$vi),
                     slab = mod$slab)

ggplot(forest_data,
       aes(x = slab, y = yi)) +
  geom_pointrange(aes(ymin = yi - se, ymax = yi + se)) +
  geom_hline(yintercept = 0, lty = 2) +
  coord_flip()


#
# theme_set(theme_bw(base_size=10))
# ata.frame(ES=ROM.ma$b,SE=ROM.ma$se,Type="Summary",Study="Summary"))
# forrest_data$Study2<-factor(forrest_data$Study, levels=rev(levels(forrest_data$Study)) )
# levels(forrest_data$Study2)
# plot1<-ggplot(data=forrest_data,aes(x=Study2,y=ES,ymax=ES+(1.96*SE),ymin=ES-(1.96*SE),size=factor(Typ
# plot2<-plot1+coord_flip()+geom_hline(aes(x=0), lty=2,size=1)+scale_size_manual(values=c(0.5,1))
# plot3<-plot2+xlab("Study")+ylab("log response ratio")+scale_colour_manual(values=c("grey","black"))
# plot3+theme(legend.position="none")
```

#USING GGPLOT

```r
df_shape$mean_age_months_centered36 <- df_shape$mean_age_months - 36
df_shape$log_mean_age_months <- log(df_shape$mean_age_months)

ggplot(df_shape, aes(x = short_cite, y = d,
                                                              ymin=d-sqrt(d_var)*1.96,
                                                              ymax=d+sqrt(d_var)*1.96)) +
  geom_pointrange(aes(color=indoeuropean), alpha = .5, position=position_dodge2(width=.5)) +
  coord_flip() +
  geom_hline(yintercept = 0, lty = 2) +
  aes(x=reorder(short_cite,-d, sum)) +
  ylab("Standardized Mean Difference (d)") +
  xlab("Citation")
```




```r
#png("secondgraph.png")
```

Looking for Asymmetry

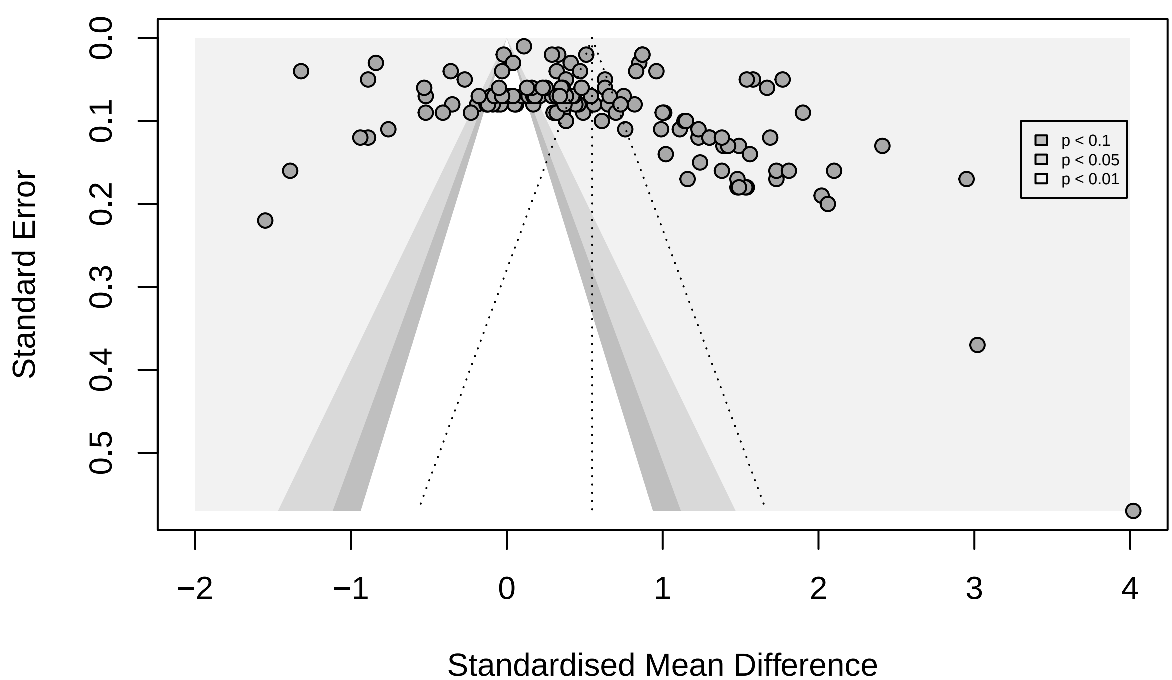
using funnel plots

```r
col.contour = c("gray75", "gray85", "gray95")

funnel(m.gen,
```

```r
       comb.random = TRUE,
       xlim = c(-2, 4),
       contour = c(0.9, 0.95, 0.99),
       col.contour = col.contour)

regtest(x = d, vi = d_var,
          data = df_shape)
```

```
##
## Regression Test for Funnel Plot Asymmetry
##
## Model:     mixed-effects meta-regression model
## Predictor: standard error
##
## Test for Funnel Plot Asymmetry: z = 6.6402, p < .0001
## Limit Estimate (as sei -> 0):   b = -0.8597 (CI: -1.2814, -0.4381)
```

```r
# Add a legend
legend(x = 3.3, y = 0.1, cex = 0.5,
       legend = c("p < 0.1", "p < 0.05", "p < 0.01"),
       fill = col.contour)
```



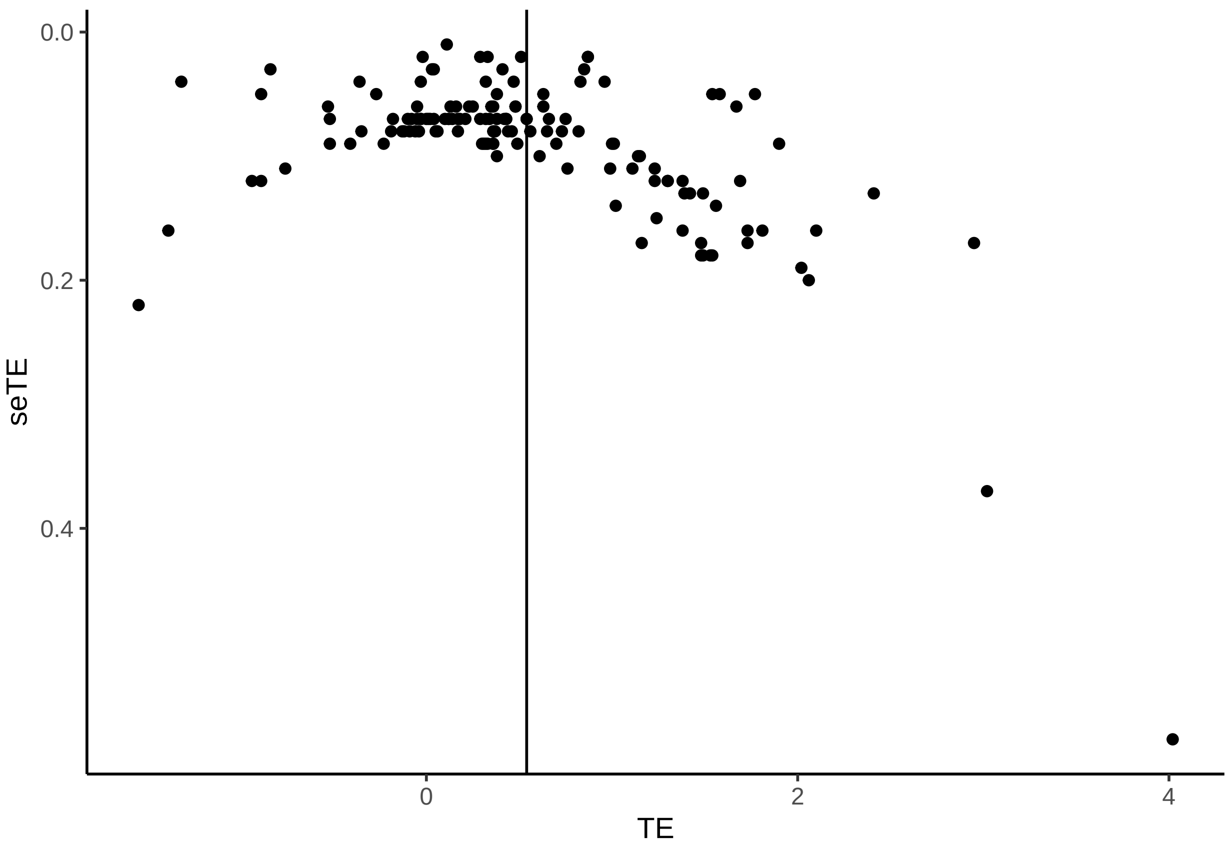

```r
#png("funnel.png")
```

funnel plots using ggplot to account for moderators:

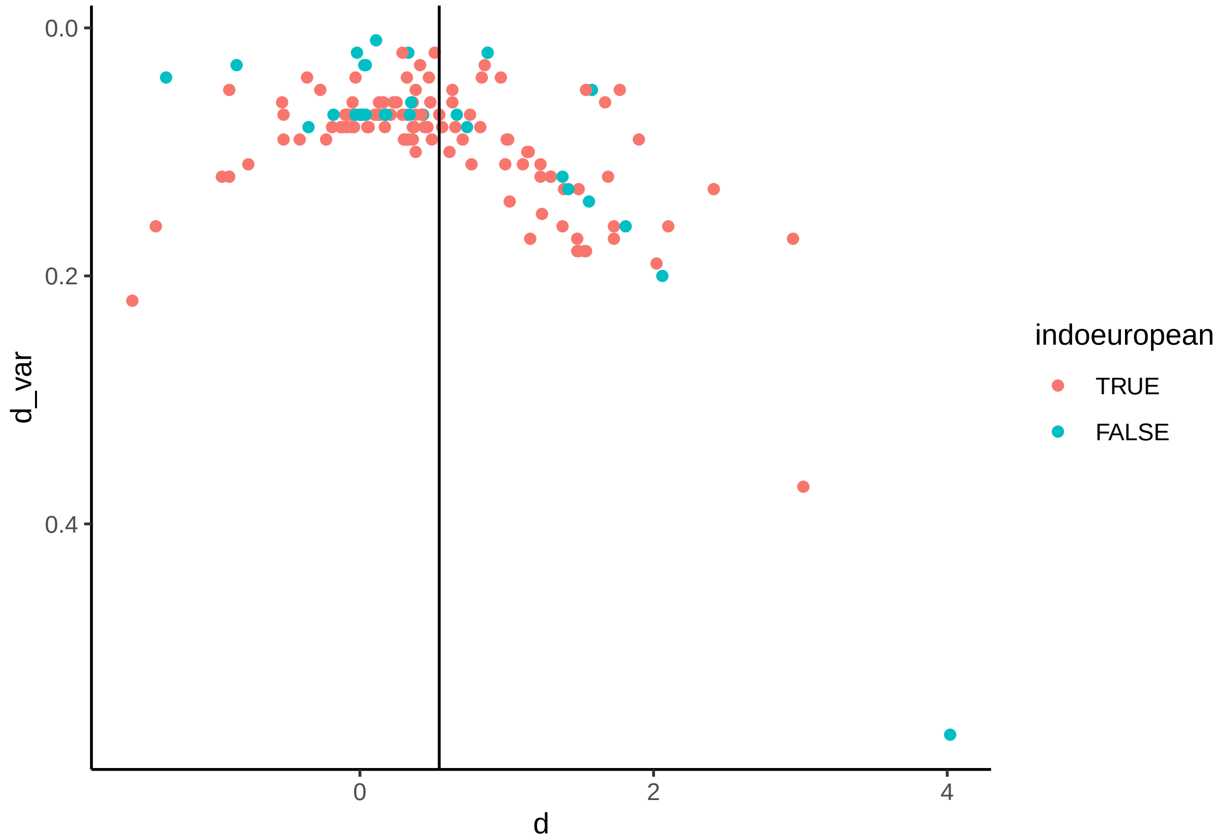
```r
x = summary(m.gen)['TE']
y = summary(m.gen)['seTE']
m.gen["TE.fixed"]
```

```
## $TE.fixed
## [1] 0.317156
```

```r
ter = m.gen["TE.random"]


data.gen = data.frame(x,y,ter)

ggplot(data = data.gen, mapping = aes(x=TE, y = seTE, color= )) +
  geom_point() +
  geom_vline(xintercept = 0.5401759) +
  scale_y_reverse()
```

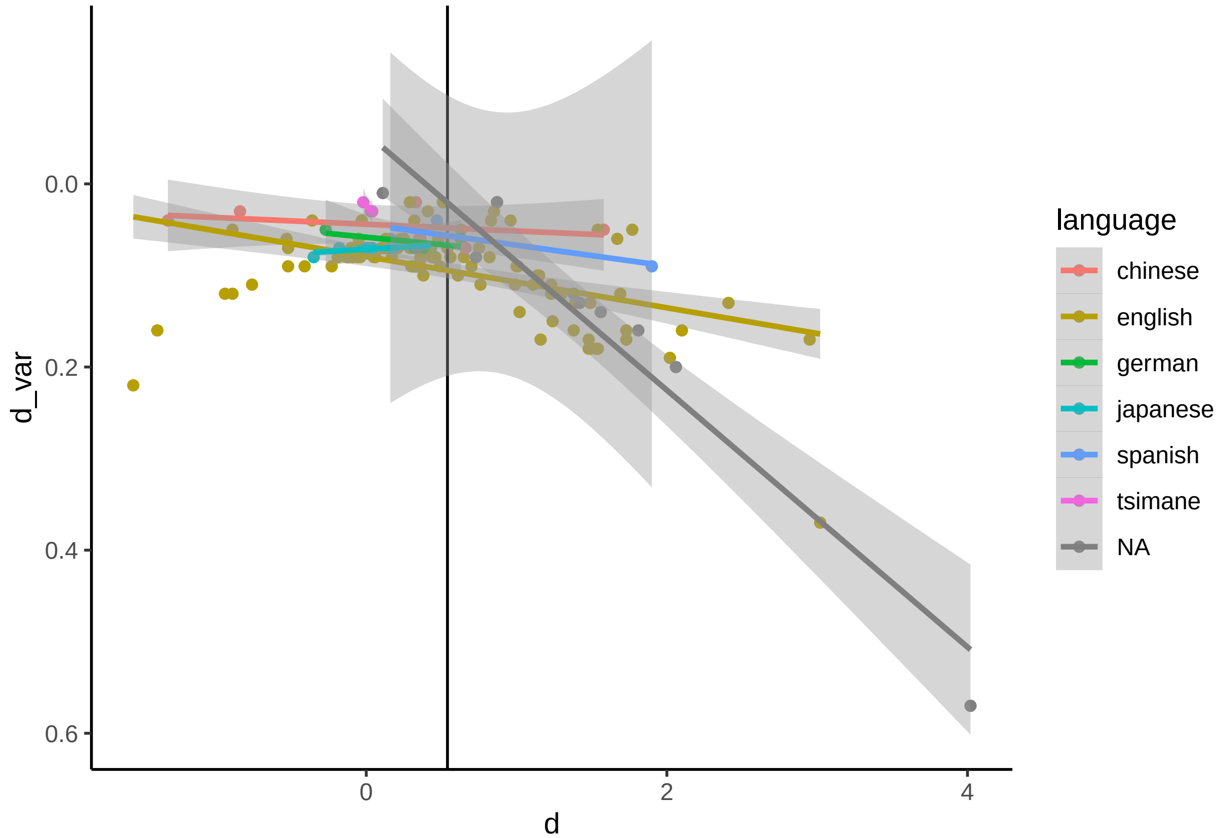



```r
ggplot(data = df_shape, mapping = aes(x=d, y = d_var, color= indoeuropean)) +
  geom_point() +
  geom_vline(xintercept = 0.5401759) +
  scale_y_reverse()
```




```
ggplot(data = df_shape, mapping = aes(x=d, y = d_var, color= language)) +
  geom_point() +
  geom_vline(xintercept = 0.5401759) +
  scale_y_reverse() +
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```
# ggplot(data = df_shape, mapping = aes(x=d, y = d_var, color= agegroup)) +
#   geom_point() +
#   geom_vline(xintercept = 0.5401759) +
#   scale_y_reverse()

# +
#   aes(x=d, y =reorder(d_var, -d), color = indoeuropean)
```

Eggers regresstion test:

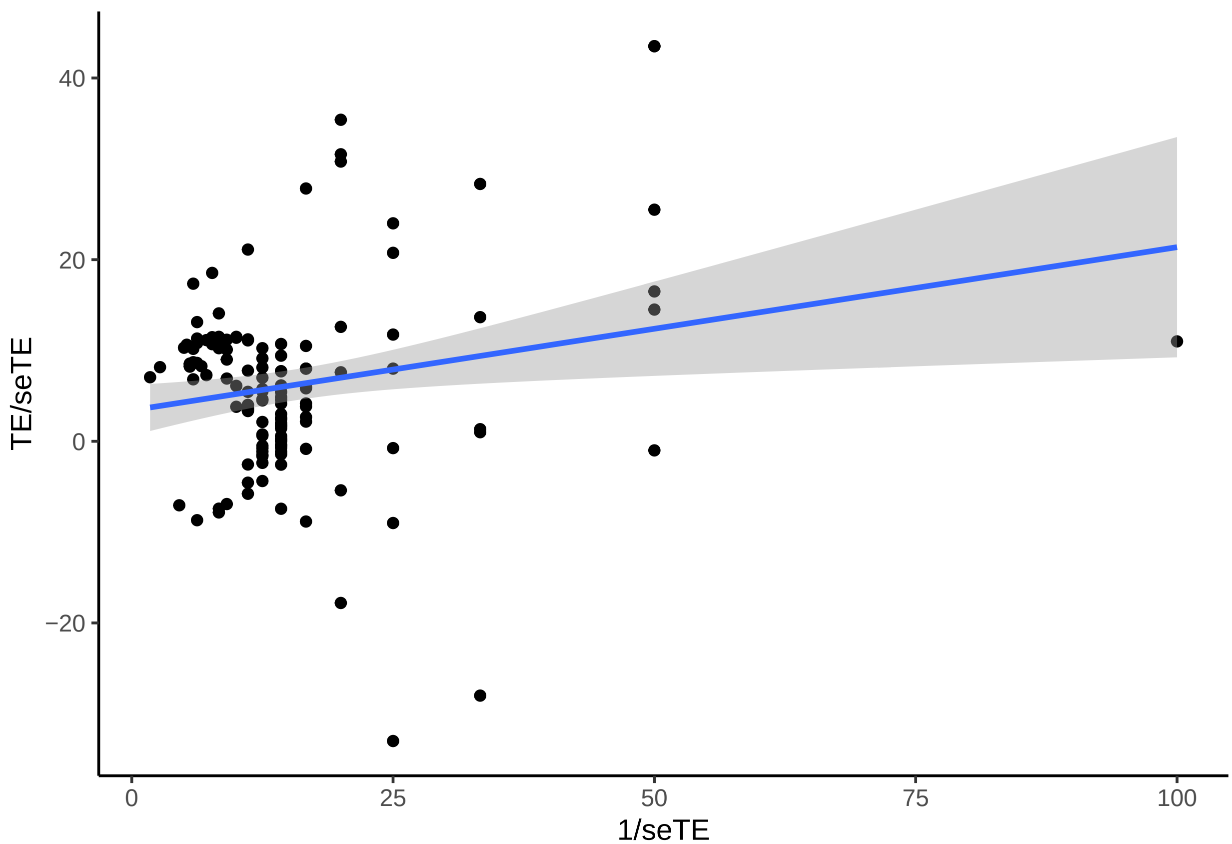
```
m.gen$data %>%
  mutate(y = m.gen$TE/m.gen$seTE, x = 1/m.gen$seTE) %>%
  lm(y ~ x, data= .) %>%
  summary()
```

```
##
## Call:
## lm(formula = y ~ x, data = .)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -40.900  -5.868   0.068   4.817  31.109
##
```

```
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.40868    1.40767   2.422   0.0168 *
## x            0.17964    0.07184   2.500   0.0136 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.2 on 138 degrees of freedom
## Multiple R-squared:  0.04334,    Adjusted R-squared:  0.03641
## F-statistic: 6.252 on 1 and 138 DF,  p-value: 0.01357
```

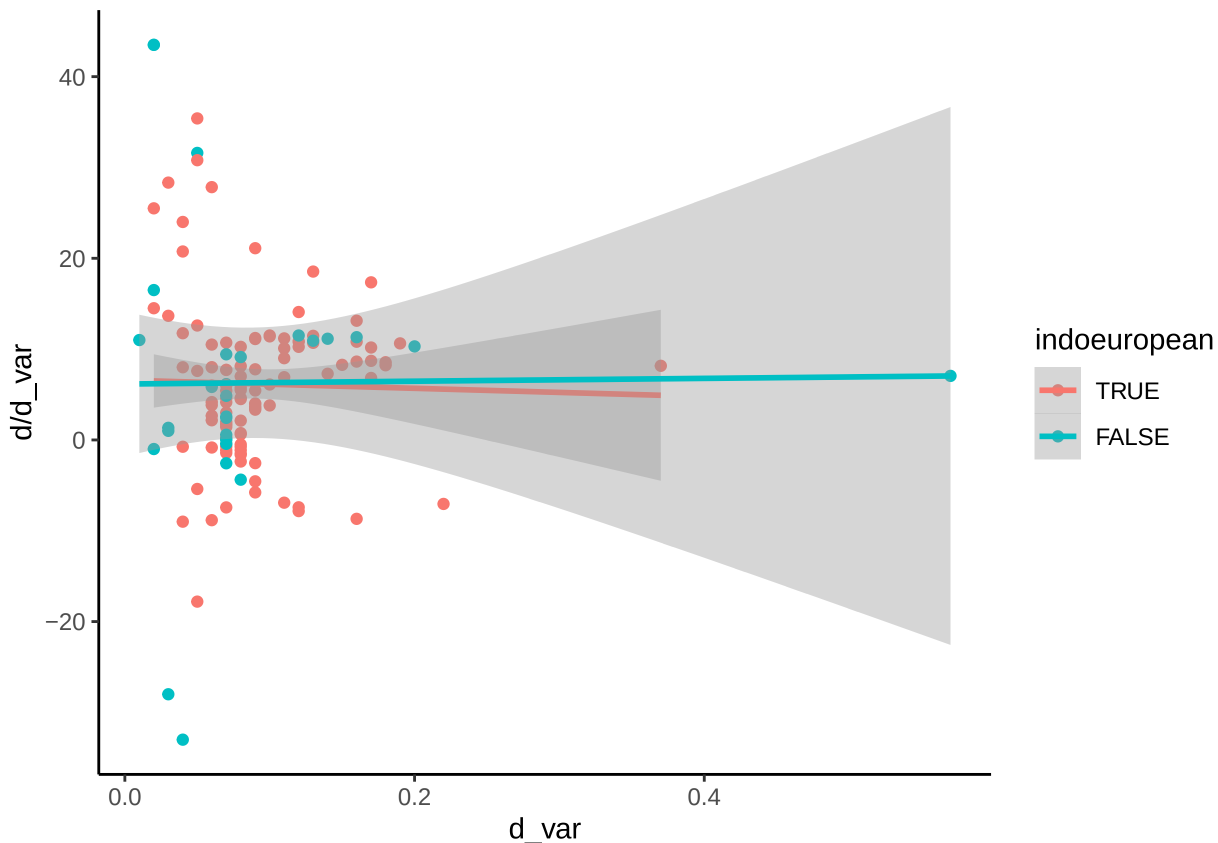
```r
#eggers regression
ggplot(data = data.gen, mapping = aes(x=1/seTE, y = TE/seTE, color= )) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```r
ggplot(data = df_shape, mapping = aes(x=d_var, y = d/d_var, color= indoeuropean)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



using rma.mv instead of m.gen

```
mod <- rma.mv(yi = d,
                  V = d_var,
                  random = ~ 1 | ID,
                  slab = short_cite,
                  data = df_shape)

mod_nested <- rma.mv(yi = d,
                  V = d_var,
                  random = ~ 1 | ID/exp_num,
                  slab = short_cite,
                  data = filter(df_shape, !is.na(exp_num)))

summary(mod)
```

```
##
## Multivariate Meta-Analysis Model (k = 140; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -345.7749   691.5499   695.5499   701.4188   695.6381
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed  factor
## sigma^2    0.1518  0.3897     25     no      ID
```

```
##
## Test for Heterogeneity:
## Q(df = 139) = 959.8543, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.4669  0.0828  5.6377  <.0001  0.3046  0.6293  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_nested)
```

```
##
## Multivariate Meta-Analysis Model (k = 133; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -328.8672   657.7344   663.7344   672.3828   663.9219
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed      factor
## sigma^2.1  0.1446  0.3803     25     no          ID
## sigma^2.2  0.0093  0.0964     34     no  ID/exp_num
##
## Test for Heterogeneity:
## Q(df = 132) = 895.1881, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.4670  0.0838  5.5735  <.0001  0.3028  0.6312  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

plotting coefficients from the rmv model: assuming that those coeffieints correspond to effect sizes

Confirmatory analysis

For primary analyses, i will exclude effect sizes from clinical populations and multilingual populations.

I will investigate the hypotheses via multi-level meta-regressions using the metafor package.

In all models, I will include random effects that control for non-independence between effect sizes based on grouping by paper and grouping by experiment.

I will first fit: Shape bias ~ 1 Shape bias ~ age shape bias ~ log(age) shape bias ~ poly(age,2)

intercept:

```r
# using the meta and metafor packages to analyze meta-analysis effect sizes
mod_intercept <- rma.mv(d ~ 1,
       V = d_var,
       random = ~1 | as.factor(Title) /
         as.factor(exp_num),
       slab = Title,
       data = filter(df_shape, !is.na(exp_num)))

summary(mod_intercept)
```

```
##
## Multivariate Meta-Analysis Model (k = 133; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -328.4943   656.9886   662.9886   671.6370   663.1761
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                               factor
## sigma^2.1  0.1519  0.3897     26     no                     as.factor(Title)
## sigma^2.2  0.0027  0.0524     34     no  as.factor(Title)/as.factor(exp_num)
##
## Test for Heterogeneity:
## Q(df = 132) = 895.1881, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.4776  0.0828  5.7691  <.0001  0.3154  0.6399  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

age

```r
mod_age <- rma.mv(d ~ mean_age_months_centered36,
       V = d_var,
       random = ~1 | as.factor(Title) /
         as.factor(exp_num),
       slab = Title,
       data = filter(df_shape, !is.na(exp_num)))
```

```
## Warning: Rows with NAs omitted from model fitting.
```

```r
summary(mod_age)
```

```
##
## Multivariate Meta-Analysis Model (k = 132; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
```

```
## -311.2327   622.4654   630.4654   641.9355   630.7854
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                                 factor
## sigma^2.1  0.1143  0.3380     25     no                       as.factor(Title)
## sigma^2.2  0.0078  0.0884     33     no  as.factor(Title)/as.factor(exp_num)
##
## Test for Residual Heterogeneity:
## QE(df = 130) = 841.0606, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 27.8175, p-val < .0001
##
## Model Results:
##
##                           estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt                     0.4438  0.0753   5.8971  <.0001   0.2963   0.5913
## mean_age_months_centered36   -0.0146  0.0028  -5.2742  <.0001  -0.0201  -0.0092
##
## intrcpt                     ***
## mean_age_months_centered36  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

log age

```
mod_log_age <- rma.mv(d ~ log_mean_age_months,
       V = d_var,
       random = ~1 | as.factor(Title) /
         as.factor(exp_num),
       slab = Title,
       data = filter(df_shape, !is.na(log_mean_age_months)))

summary(mod_log_age)
```

```
##
## Multivariate Meta-Analysis Model (k = 132; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -315.7124   631.4248   639.4248   650.8949   639.7448
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                                 factor
## sigma^2.1  0.1183  0.3439     25     no                       as.factor(Title)
## sigma^2.2  0.0059  0.0767     33     no  as.factor(Title)/as.factor(exp_num)
##
## Test for Residual Heterogeneity:
## QE(df = 130) = 851.6190, p-val < .0001
##
```

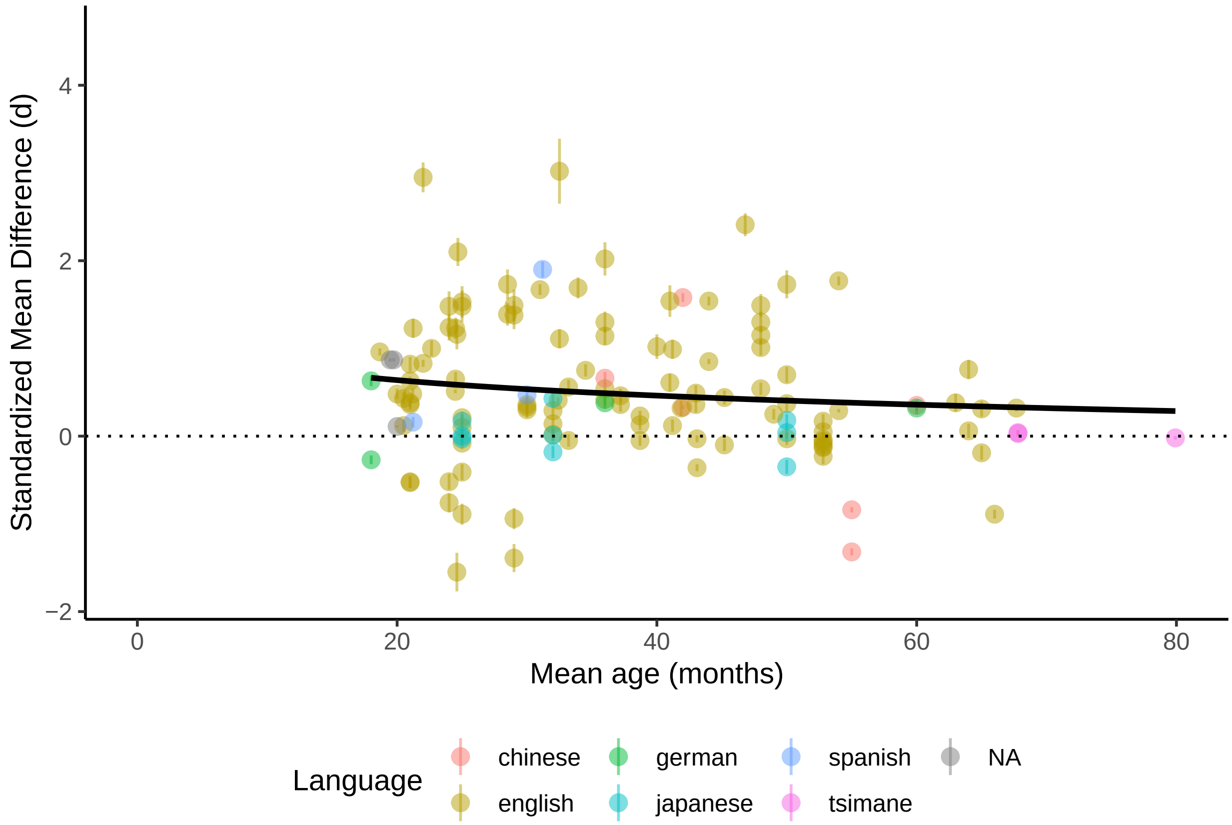
```
## Test of Moderators (coefficient 2):
## QM(df = 1) = 18.6968, p-val < .0001
##
## Model Results:
##
##                      estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt                2.0909  0.3879   5.3904  <.0001   1.3307   2.8512  ***
## log_mean_age_months   -0.4711  0.1089  -4.3240  <.0001  -0.6846  -0.2575  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Let's look at what this means:

```
ggplot(df_shape,
       aes(x = mean_age_months, y = d, color = language))+
  geom_pointrange(aes(ymin = d - d_var, ymax = d + d_var),
                  alpha = .5) +
  geom_smooth(aes(group = 1),
              col = "black",
              method = "lm", se = FALSE,
              formula = y ~ log(x)) +
  geom_hline(yintercept = 0, lty = 3) +
  ylab("Standardized Mean Difference (d)") +
  xlab("Mean age (months)") +
  scale_color_discrete(name = "Language") +
  scale_linetype_discrete(name = "Indo-European") +
  theme(legend.position = "bottom") +
  xlim(0,80)
```

```
## Warning: Removed 8 rows containing non-finite values (`stat_smooth()`).
```

```
## Warning: Removed 8 rows containing missing values (`geom_pointrange()`).
```



polynmoial age

```
mod_poly <- rma.mv(d ~ mean_age_months_centered36 + I(mean_age_months_centered36^2),
       V = d_var,
       random = ~1 | as.factor(Title) /
         as.factor(exp_num),
       slab = Title,
       data = filter(df_shape, !is.na(log_mean_age_months)))

summary(mod_poly)
```

```
##
## Multivariate Meta-Analysis Model (k = 132; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -303.1769   606.3538   616.3538   630.6528   616.8416
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                               factor
## sigma^2.1  0.0984  0.3138     25     no                     as.factor(Title)
## sigma^2.2  0.0423  0.2056     33     no  as.factor(Title)/as.factor(exp_num)
##
## Test for Residual Heterogeneity:
```

```
## QE(df = 129) = 829.1803, p-val < .0001
##
## Test of Moderators (coefficients 2:3):
## QM(df = 2) = 45.6512, p-val < .0001
##
## Model Results:
##
##                                  estimate      se     zval    pval    ci.lb
## intrcpt                            0.6197  0.0892   6.9485  <.0001   0.4449
## mean_age_months_centered36        -0.0048  0.0037  -1.2926  0.1961  -0.0121
## I(mean_age_months_centered36^2)   -0.0007  0.0002  -4.1852  <.0001  -0.0011
##                                    ci.ub
## intrcpt                           0.7945  ***
## mean_age_months_centered36        0.0025
## I(mean_age_months_centered36^2)  -0.0004  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m.gen.reg <- metareg(m.gen, ~language)
```

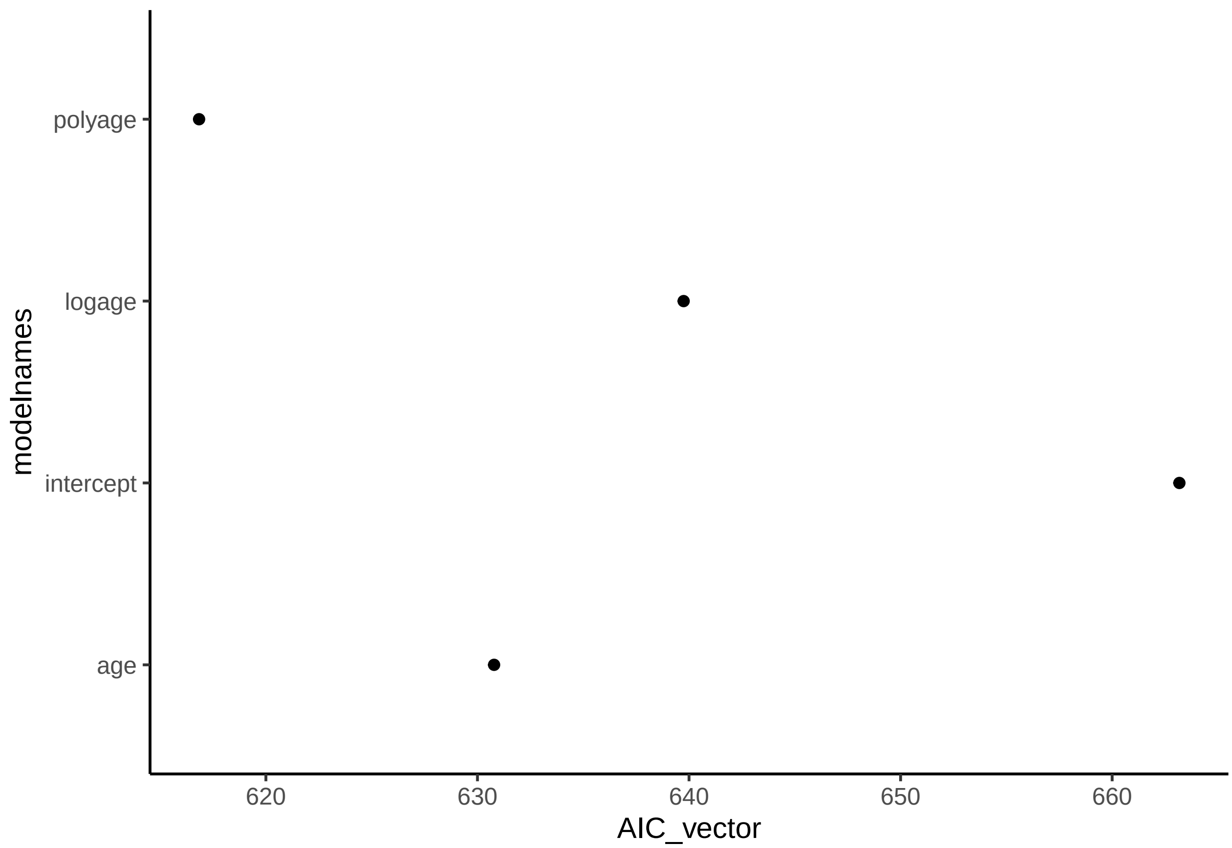
```
## Warning: Studies with NAs omitted from model fitting.
```

model comparison and plotting AICc , what is the criteria ? cutoff

```
#anova(mod_log_age, mod_poly, refit = TRUE)
#anova(mod_age, mod_poly) ## the two models are not comparable, not nested

#plot_component(mod, type = "BIC")
summary(mod_intercept)$fit.stats[5,'REML']
```

```
## [1] 663.1761
```

```
AIC_vector <- c(summary(mod_intercept)$fit.stats[5,'REML'],
                summary(mod_age)$fit.stats[5,'REML'],
                summary(mod_log_age)$fit.stats[5,'REML'],
                summary(mod_poly)$fit.stats[5,'REML'])

# AIC_vector <- c(AICc(mod_intercept), AICc(mod_age), AICc(mod_log_age), AICc(mod_poly))

modelnames <- c("intercept", "age", "logage", "polyage")

data.AIC = data.frame(AIC_vector, modelnames)

ggplot(data = data.AIC, mapping = aes(x = AIC_vector, y = modelnames)) +
  geom_point()
```



setting the contrasts:

```
#
# df_shape = df_shape %>%
#   mutate(lang_contrast = factor(language,
#                                levels = c("english", "chinese", "german", "japanese",
#                                           "tsimane", "spanish"),
#                                labels = c(0,-1,1,1,1,1)),
#          lang_contrast = lang_contrast %>%
#            as.character() %>%
#            as.factor() )
# contrasts(df_shape$lang_contrast) <- contr.sum(6)
# df_shape$lang_contrast
```

```
df_shape$lang_factor <- as.factor(df_shape$language)
# contrasts(df_shape$lang_factor) <- contr.treatment(6, base = 2)
df_shape$lang_factor <- fct_relevel(df_shape$lang_factor, "english", after = Inf)
contrasts(df_shape$lang_factor) <- contr.sum(6)*0.5
```

poly age with language

```
age_lang <- rma.mv(d ~ poly(mean_age_months_centered36,2) + language ,
                  V = d_var,
```

```r
                  random = ~ 1 | ID/exp_num/language,
                  slab = short_cite,
                  data = filter(df_shape, !is.na(exp_num), !is.na(language)))

age_lang_interact <- rma.mv(d ~ poly(mean_age_months_centered36,2) * language,
                  V = d_var,
                  random = ~ 1 | ID/exp_num/language,
                  slab = short_cite,
                  data = filter(df_shape, !is.na(exp_num), !is.na(language)))
```

orthogonal polynomial:

```
## Warning: Redundant predictors dropped from the model.
```

```r
age_lang %>% summary()
```

```
##
## Multivariate Meta-Analysis Model (k = 129; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -245.7844   491.5689   513.5689   544.3226   515.9909
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed              factor
## sigma^2.1  0.0000  0.0001     23     no                  ID
## sigma^2.2  0.0000  0.0000     32     no          ID/exp_num
## sigma^2.3  0.2284  0.4779     38     no  ID/exp_num/language
##
## Test for Residual Heterogeneity:
## QE(df = 121) = 747.7508, p-val < .0001
##
## Test of Moderators (coefficients 2:8):
## QM(df = 7) = 60.5375, p-val < .0001
##
## Model Results:
##
##                                      estimate      se     zval    pval
## intrcpt                                0.2658  0.3539   0.7509  0.4527
## poly(mean_age_months_centered36, 2)1  -2.4837  0.4782  -5.1942  <.0001
## poly(mean_age_months_centered36, 2)2  -2.4701  0.4897  -5.0445  <.0001
## languageenglish                        0.2381  0.3675   0.6478  0.5171
## languagegerman                         0.0743  0.5087   0.1460  0.8839
## languagejapanese                      -0.3264  0.6015  -0.5426  0.5874
## languagespanish                        0.3954  0.4747   0.8329  0.4049
## languagetsimane                        1.0230  0.4889   2.0925  0.0364
##                                        ci.lb    ci.ub
## intrcpt                              -0.4279   0.9595
## poly(mean_age_months_centered36, 2)1 -3.4209  -1.5465  ***
## poly(mean_age_months_centered36, 2)2 -3.4298  -1.5103  ***
## languageenglish                      -0.4823   0.9585
## languagegerman                       -0.9228   1.0714
## languagejapanese                     -1.5053   0.8525
```

```
## languagespanish                         -0.5350   1.3258
## languagetsimane                          0.0648   1.9813    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
age_lang_interact %>% summary()
```

```
##
## Multivariate Meta-Analysis Model (k = 129; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -225.6627   451.3255   491.3255   545.6955   500.5563
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.1811  0.4255     23     no                   ID
## sigma^2.2  0.0000  0.0000     32     no           ID/exp_num
## sigma^2.3  0.0511  0.2261     38     no  ID/exp_num/language
##
## Test for Residual Heterogeneity:
## QE(df = 112) = 672.2426, p-val < .0001
##
## Test of Moderators (coefficients 2:17):
## QM(df = 16) = 110.5441, p-val < .0001
##
## Model Results:
##
##                                                      estimate        se
## intrcpt                                                0.4417    1.3571
## poly(mean_age_months_centered36, 2)1                 -10.3159   11.4326
## poly(mean_age_months_centered36, 2)2                  -2.5398   13.9288
## languageenglish                                        0.1191    1.3708
## languagegerman                                        -0.5372    1.1569
## languagejapanese                                      -0.1032    1.4090
## languagespanish                                       59.6411   16.7230
## languagetsimane                                       -2.1232    7.1494
## poly(mean_age_months_centered36, 2)1:languageenglish    8.4474   11.4157
## poly(mean_age_months_centered36, 2)2:languageenglish    0.5605   13.9160
## poly(mean_age_months_centered36, 2)1:languagegerman     9.3529   12.3000
## poly(mean_age_months_centered36, 2)2:languagegerman     3.2744   15.0504
## poly(mean_age_months_centered36, 2)1:languagejapanese   9.1295   11.6640
## poly(mean_age_months_centered36, 2)2:languagejapanese   1.3671   14.4083
## poly(mean_age_months_centered36, 2)1:languagespanish  977.1301  271.1465
## poly(mean_age_months_centered36, 2)2:languagespanish  450.2977  129.0468
## poly(mean_age_months_centered36, 2)1:languagetsimane   20.1719   46.8774
##                                                          zval    pval
## intrcpt                                                0.3254  0.7449
## poly(mean_age_months_centered36, 2)1                  -0.9023  0.3669
## poly(mean_age_months_centered36, 2)2                  -0.1823  0.8553
## languageenglish                                        0.0869  0.9308
## languagegerman                                        -0.4643  0.6424
## languagejapanese                                      -0.0732  0.9416
```

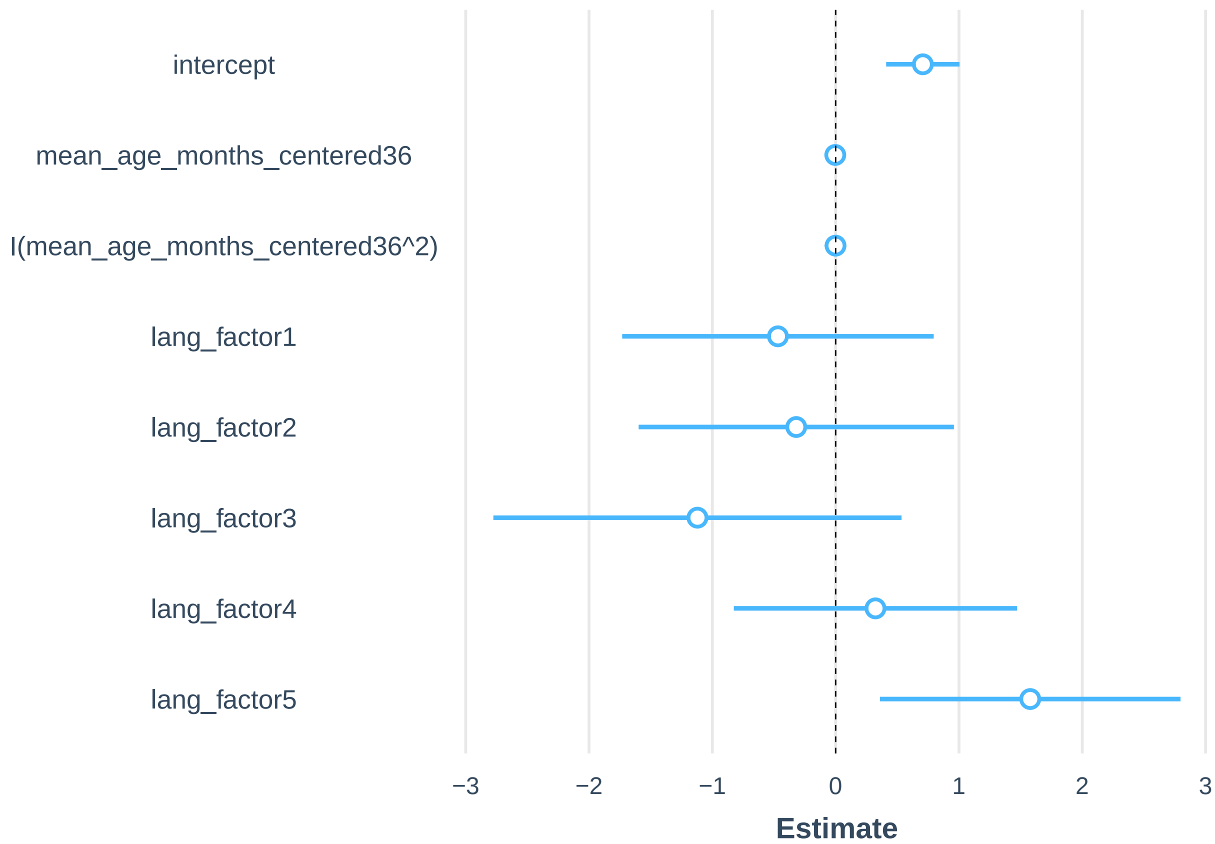
```
## languagespanish                                        3.5664  0.0004
## languagetsimane                                       -0.2970  0.7665
## poly(mean_age_months_centered36, 2)1:languageenglish    0.7400  0.4593
## poly(mean_age_months_centered36, 2)2:languageenglish    0.0403  0.9679
## poly(mean_age_months_centered36, 2)1:languagegerman     0.7604  0.4470
## poly(mean_age_months_centered36, 2)2:languagegerman     0.2176  0.8278
## poly(mean_age_months_centered36, 2)1:languagejapanese   0.7827  0.4338
## poly(mean_age_months_centered36, 2)2:languagejapanese   0.0949  0.9244
## poly(mean_age_months_centered36, 2)1:languagespanish    3.6037  0.0003
## poly(mean_age_months_centered36, 2)2:languagespanish    3.4894  0.0005
## poly(mean_age_months_centered36, 2)1:languagetsimane    0.4303  0.6670
##                                                          ci.lb      ci.ub
## intrcpt                                                 -2.2183     3.1016
## poly(mean_age_months_centered36, 2)1                   -32.7234    12.0916
## poly(mean_age_months_centered36, 2)2                   -29.8397    24.7601
## languageenglish                                         -2.5676     2.8058
## languagegerman                                          -2.8046     1.7303
## languagejapanese                                        -2.8647     2.6584
## languagespanish                                         26.8646    92.4176  ***
## languagetsimane                                        -16.1357    11.8894
## poly(mean_age_months_centered36, 2)1:languageenglish   -13.9269    30.8217
## poly(mean_age_months_centered36, 2)2:languageenglish   -26.7144    27.8355
## poly(mean_age_months_centered36, 2)1:languagegerman    -14.7547    33.4605
## poly(mean_age_months_centered36, 2)2:languagegerman    -26.2238    32.7726
## poly(mean_age_months_centered36, 2)1:languagejapanese  -13.7316    31.9905
## poly(mean_age_months_centered36, 2)2:languagejapanese  -26.8727    29.6070
## poly(mean_age_months_centered36, 2)1:languagespanish   445.6927  1508.5675  ***
## poly(mean_age_months_centered36, 2)2:languagespanish   197.3706   703.2247  ***
## poly(mean_age_months_centered36, 2)1:languagetsimane   -71.7061   112.0498
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
age_lang_npoly <- rma.mv(d ~ mean_age_months_centered36 + I(mean_age_months_centered36^2) + lang_factor
                  V = d_var,
                  random = ~ 1 | ID/exp_num/language,
                  slab = short_cite,
                  data = filter(df_shape, !is.na(exp_num), !is.na(language)))


age_lang_interact_npoly <- rma.mv(d ~ mean_age_months_centered36 * lang_factor +
                                    I(mean_age_months_centered36^2) * lang_factor,
                  V = d_var,
                  random = ~ 1 | ID/exp_num/lang_factor,
                  slab = short_cite,
                  data = filter(df_shape, !is.na(exp_num), !is.na(language)))
```

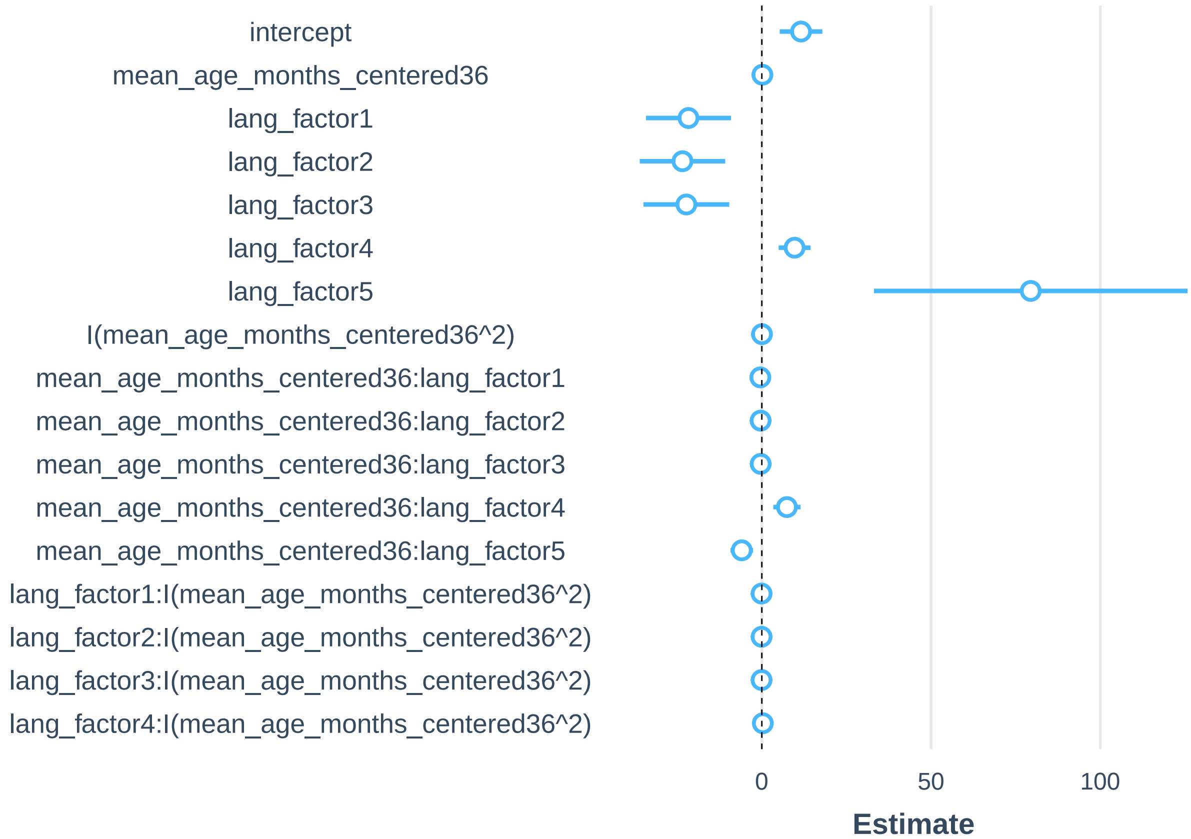
the other polynomial:

```
## Warning: Redundant predictors dropped from the model.
```

```r
plot_summs(age_lang_npoly, robust = TRUE)
```




```r
plot_summs(age_lang_interact_npoly, robust = TRUE)
```




```
age_lang_npoly %>% summary()
```

```
##
## Multivariate Meta-Analysis Model (k = 129; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -245.7844   491.5689   513.5689   544.3226   515.9909
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                factor
## sigma^2.1  0.0000  0.0001     23     no                    ID
## sigma^2.2  0.0000  0.0000     32     no            ID/exp_num
## sigma^2.3  0.2284  0.4779     38     no   ID/exp_num/language
##
## Test for Residual Heterogeneity:
## QE(df = 121) = 747.7508, p-val < .0001
##
## Test of Moderators (coefficients 2:8):
## QM(df = 7) = 60.5375, p-val < .0001
##
## Model Results:
##
##                                         estimate      se     zval    pval    ci.lb
## intrcpt                                   0.7069  0.1518   4.6572  <.0001   0.4094
```

```
## mean_age_months_centered36        -0.0033  0.0040  -0.8159  0.4146  -0.0112
## I(mean_age_months_centered36^2)   -0.0010  0.0002  -5.0445  <.0001  -0.0014
## lang_factor1                      -0.4681  0.6445  -0.7264  0.4676  -1.7313
## lang_factor2                      -0.3196  0.6522  -0.4900  0.6242  -1.5979
## lang_factor3                      -1.1209  0.8445  -1.3274  0.1844  -2.7761
## lang_factor4                       0.3226  0.5860   0.5506  0.5819  -0.8259
## lang_factor5                       1.5779  0.6218   2.5376  0.0112   0.3592
##                                    ci.ub
## intrcpt                           1.0044  ***
## mean_age_months_centered36        0.0046
## I(mean_age_months_centered36^2)  -0.0006  ***
## lang_factor1                      0.7951
## lang_factor2                      0.9588
## lang_factor3                      0.5342
## lang_factor4                      1.4712
## lang_factor5                      2.7967    *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
age_lang_interact_npoly %>% summary()
```

```
##
## Multivariate Meta-Analysis Model (k = 129; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -225.6627   451.3255   491.3255   545.6955   500.5563
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.1811  0.4255     23     no                      ID
## sigma^2.2  0.0000  0.0000     32     no              ID/exp_num
## sigma^2.3  0.0511  0.2261     38     no  ID/exp_num/lang_factor
##
## Test for Residual Heterogeneity:
## QE(df = 112) = 672.2426, p-val < .0001
##
## Test of Moderators (coefficients 2:17):
## QM(df = 16) = 110.5441, p-val < .0001
##
## Model Results:
##
##                                              estimate       se     zval
## intrcpt                                       11.5861   3.2177   3.6007
## mean_age_months_centered36                     0.1694   0.0584   2.9008
## lang_factor1                                 -21.6791   6.4096  -3.3823
## lang_factor2                                 -23.4460   6.4433  -3.6388
## lang_factor3                                 -22.2984   6.4700  -3.4465
## lang_factor4                                   9.6867   2.4130   4.0144
## lang_factor5                                  79.4585  23.6312   3.3624
## I(mean_age_months_centered36^2)                0.0368   0.0107   3.4326
## mean_age_months_centered36:lang_factor1       -0.4441   0.2321  -1.9137
## mean_age_months_centered36:lang_factor2       -0.3584   0.1317  -2.7207
```

```
## mean_age_months_centered36:lang_factor3        -0.3419   0.1172  -2.9172
## mean_age_months_centered36:lang_factor4         7.4139   2.0579   3.6026
## mean_age_months_centered36:lang_factor5        -5.9271   1.7075  -3.4711
## lang_factor1:I(mean_age_months_centered36^2)   -0.0758   0.0234  -3.2456
## lang_factor2:I(mean_age_months_centered36^2)   -0.0731   0.0216  -3.3801
## lang_factor3:I(mean_age_months_centered36^2)   -0.0747   0.0216  -3.4570
## lang_factor4:I(mean_age_months_centered36^2)    0.2989   0.0854   3.4989
##                                                 pval     ci.lb     ci.ub
## intrcpt                                       0.0003    5.2795   17.8926  ***
## mean_age_months_centered36                    0.0037    0.0549    0.2838   **
## lang_factor1                                  0.0007  -34.2416   -9.1166  ***
## lang_factor2                                  0.0003  -36.0748  -10.8173  ***
## lang_factor3                                  0.0006  -34.9792   -9.6175  ***
## lang_factor4                                  <.0001    4.9573   14.4161  ***
## lang_factor5                                  0.0008   33.1422  125.7749  ***
## I(mean_age_months_centered36^2)               0.0006    0.0158    0.0579  ***
## mean_age_months_centered36:lang_factor1       0.0557   -0.8989    0.0107    .
## mean_age_months_centered36:lang_factor2       0.0065   -0.6165   -0.1002   **
## mean_age_months_centered36:lang_factor3       0.0035   -0.5716   -0.1122   **
## mean_age_months_centered36:lang_factor4       0.0003    3.3804   11.4473  ***
## mean_age_months_centered36:lang_factor5       0.0005   -9.2738   -2.5804  ***
## lang_factor1:I(mean_age_months_centered36^2)  0.0012   -0.1216   -0.0300   **
## lang_factor2:I(mean_age_months_centered36^2)  0.0007   -0.1154   -0.0307  ***
## lang_factor3:I(mean_age_months_centered36^2)  0.0005   -0.1170   -0.0323  ***
## lang_factor4:I(mean_age_months_centered36^2)  0.0005    0.1314    0.4663  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

poly age with syntax

```
age_lang_syntax <- rma.mv(d ~ poly(mean_age_months,2) + language + Informative_syntax,
                  V = d_var,
                  random = ~ 1 | ID/exp_num/language,
                  slab = short_cite,
                  data = filter(df_shape, !is.na(exp_num), !is.na(language)))
```

```
## Warning: Rows with NAs omitted from model fitting.
```

```
rma.mv(d ~ poly(mean_age_months,2)*Informative_syntax,
       V = d_var,
       random = ~1 | as.factor(Title) +
         as.factor(exp_num),
       slab = Title,
       data = filter(df_shape, !is.na(mean_age_months))) %>% glance()
```

```
## Warning: Rows with NAs omitted from model fitting.
```

```
## Warning: One or more levels of inner factor (i.e., The shape-bias in
## Spanish-speaking children and its relationship to vocabulary) removed due to
## NAs.
```

```
## # A tibble: 1 x 12
##   tau.squ~1 cochr~2 p.valu~3 cochr~4 p.valu~5 df.re~6 logLik devia~7   AIC   BIC
##       <dbl>   <dbl>    <dbl>   <dbl>    <dbl>   <int>  <dbl>   <dbl> <dbl> <dbl>
## 1     0.214    801. 1.47e-99    53.1 3.24e-10     124  -294.    588.  604.  627.
## # ... with 2 more variables: AICc <dbl>, nobs <int>, and abbreviated variable
## #   names 1: tau.squared, 2: cochran.qe, 3: p.value.cochran.qe, 4: cochran.qm,
## #   5: p.value.cochran.qm, 6: df.residual, 7: deviance
```

Exploratory analysis

```r
rma.mv(d ~ poly(mean_age_months,2),
       V = d_var,
       random = ~1 | as.factor(language)+
         as.factor(Title),
       slab = Title,
       data = filter(df_shape, !is.na(mean_age_months), !is.na(language))) %>% glance()
```

```
## # A tibble: 1 x 12
##   tau.squ~1 cochr~2 p.valu~3 cochr~4 p.valu~5 df.re~6 logLik devia~7   AIC   BIC
##       <dbl>   <dbl>    <dbl>   <dbl>    <dbl>   <int>  <dbl>   <dbl> <dbl> <dbl>
## 1     0.206    800. 1.59e-98    41.5 9.66e-10     126  -254.    508.  518.  532.
## # ... with 2 more variables: AICc <dbl>, nobs <int>, and abbreviated variable
## #   names 1: tau.squared, 2: cochran.qe, 3: p.value.cochran.qe, 4: cochran.qm,
## #   5: p.value.cochran.qm, 6: df.residual, 7: deviance
```

Discussion

References