How does the human auditory system become expert in speech processing? Insights from development.

Cécile Issard and Alejandrina Cristia

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- Target journal: Developmental science
- Article type: short report
- 4000 words
- 6 keywords
- Running title: 40 characters
- Submit one normal and one blinded version
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Main text file:

1. Title
2. Research highlights
3. Abstract and key words
4. Main
5. References
6. Figures and tables (each clearly identified, labelled and on a separate page)
7. Appendices (if relevant).

Introduction

A long line of research shows that infants process speech preferentially over other types of sounds. As the main signal for vocal communication, speech must be special for humans. Readily from birth, humans would be equipped with an auditory module dedicated to speech sounds, to process them with dedicated auditory and cognitive mechanisms. This preference has been investigated by numerous studies, contrasting speech to a variety of sounds, from white noise to backward speech, and at different ages. Getting a precise overview of this capacity is therefore difficult. "broader template that initially encompasses vocalizations of human and nonhuman primates and is rapidly tuned specifically to human vocalizations." "Is this link sufficiently broad to include naturalistic vocalizations beyond those of our closest genealogical cousins, or is it restricted to primates, whose vocalizations may be perceptually just close enough to our own to serve as early candidates for the platform on which human language is launched?" (Ferry et al., 2013) The auditory literature suggests that natural sounds are processed differently by the auditory system (e.g. Mezhrahi & Nelken, 2014). Extending to language acquisition, naturalness is a key factor for word segmentation (Black and Bergman, 2016). Speech might therefore not be prefered per se, but because it belongs to a broader category of natural, own-species, or communicative sounds.

```
To answer this question, we conducted a meta-analysis investigating infants' preference for speech sound
```

```r
# Comment out next set of lines for RECALCULATION
require(RCurl)
u <- "https://docs.google.com/spreadsheets/d/e/2PACX-1vRzzqtgNdfoKTMqb4bWyy5LyH5XdrOEy4sl3VNDCnGIyvdrn
tc <- getURL(u, ssl.verifypeer=FALSE)
DB <- read.csv(textConnection(tc))
write.csv(DB,"MA_speech_pref_data.csv")
```

```r
# Uncomment next line for OFFLINE MODE
#DB <- read.csv("MA_speech_pref_data.csv", header = T, sep = ",", na.strings = "")

## of datapoints and variables coded
dim(DB)
```

```
## [1] 90 53
```

```r
## FIX, remove empty columns
rmcol=NULL
for(mycol in 1:dim(DB)[2]) if(sum(is.na(DB[,mycol]))==length(DB[,mycol])) rmcol=c(rmcol,colnames(DB)[myc
rmcol[!(rmcol %in% "corr")]->rmcol
DB[,!(colnames(DB) %in% rmcol)]->DB
dim(DB)
```

```
## [1] 90 41
```

```r
## FIX, DOUBLE CHECK ALEX & CECILE !! REPLACE ALL EMPTY WITH NA
for(mycol in colnames(DB)) DB[DB[,mycol]=="" & !is.na(DB[,mycol]),mycol]<-NA
for(mycol in c("naturalness","social2","species2","test_lang")) DB[,mycol]<-factor(DB[,mycol])
summary(DB)
```

```
##                  study_ID
##  shultz2010        :12
##  Ecklund-Flores1996:10
##  may2018           : 8
##  mcdonald2019      : 8
##  vouloumanos2009   : 7
##  shultz2014        : 5
##  (Other)           :40
##
##  Shultz, A., & Vouloumanos, A. (2010). Three-Month-Olds Prefer Speech to Other Naturally Occurring Si
##  Ecklundâ€<90>Flores, L. and Turkewitz, G. (1996). Asymmetric headturning to speech and nonspeech in
##  May L., Gervain J., Carreiras M., Werker J.F. (2019).The specificity of the neural response to speec
##  Mc Donald, N. M., Perdue, K. L., Eilbott, J., Loyal, J., Shic, F., Pelphrey, K. A. (2019). Infant br
##  Vouloumanos, A., Druhen, M. J., Hauser, M. D., & Huizink, A. T. (2009). Five-month-old infants' iden
##  Shultz, S., Vouloumanos, A., Bennett, R. H., Pelphrey, K. (2014). Neural specialization for speech i
##  (Other)
##                                 short_cite peer_reviewed coder
##  Shultz & Vouloumanos (2010)        :12   yes:90        CI:90
##  Ecklund-Flores and Turkewitz (1996):10
##  May et al. (2018)                  : 8
##  Mc Donald et al. (2019)            : 8
##  Vouloumanos et al. (2009)          : 7
##  Shultz et al. (2014)               : 5
##  (Other)                            :40
##                                    location  participant_age
##  yale                                  :25   infant:90
##  49Â° 15â€² nord, 123Â° 06â€² ouest    :12
##  40Â° 42â€² 52â€³ N, 74Â° 00â€² 22â€³ W:10
##  tokyo                                 : 8
##  49Â° 15â€² N, 123Â° 06â€² W           : 5
##  (Other)                               :16
##  NA's                                  :14
##        same_infant    expt_num                     expt_condition method
##  mcdonald2019: 8   Min.   :1.000   fwd_vs_backward_foreign: 8     CF :36
```

```
## shultz2014  : 5   1st Qu.:1.000   speech_vs_monkey       : 5     HAS: 4
## anonymous1  : 4   Median :1.000   speech_vs_SWS          : 5     HPP:10
## cristia2014 : 4   Mean   :1.611   fwd_vs_backward        : 4     PL :40
## may2011     : 4   3rd Qu.:2.000   fwd_vs_backward_native : 4
## may2018_1   : 4   Max.   :5.000   IDS_vs_H-Communicative : 4
## (Other)     :61                   (Other)                :60
##  participant_design      response_mode      exposure_phase  infant_type
## within_one: 1       behavior    :19    conditioning:12     typical:90
## within_two:89       eye-tracking:31    habituation : 1
##                     NIRS        :40    test_only   :77
##
##
##
##
##      dependent_measure      n_1         mean_age_1
## looking_time  :36      Min.   : 8.0   Min.   :  1.460
## mean_amplitude:39      1st Qu.:14.0   1st Qu.:  1.879
## pc_head_turns :10      Median :22.0   Median : 94.530
## peak_amplitude: 1      Mean   :22.1   Mean   : 90.004
## sucking_time  : 4      3rd Qu.:26.5   3rd Qu.:149.010
##                        Max.   :60.0   Max.   :380.500
##
##  age_range_1        n_excluded_1      gender_1         speech_only.voc
## Min.   :  0.9167   Min.   : 2.00   Min.   :0.2857   speech_only:90
## 1st Qu.:  3.0000   1st Qu.: 3.20   1st Qu.:0.3529
## Median : 18.9400   Median :10.00   Median :0.4074
## Mean   : 31.5062   Mean   :11.38   Mean   :0.4223
## 3rd Qu.: 38.0000   3rd Qu.:17.00   3rd Qu.:0.4750
## Max.   :409.7200   Max.   :44.00   Max.   :0.7000
## NA's   :3          NA's   :9       NA's   :43
##     naturalness           species              species2   social
## artificial:41                 : 0   conspecific   :19       : 0
## natural   :42   conspecific   :47   heterospecific:14   no  :51
## NA's      : 7   heterospecific:14   NA's          :57   yes :32
##                 NA's          :29                       NA's: 7
##
##
##
## social2    voc_non.voc   test_lang
## no  :19          : 0   foreign:40
## yes :23   non-voc:54   native :36
## NA's:48   voc    :29   NA's   :14
##           NA's   : 7
##
##
##
##                                                          notes.code
## Left hemisphere                                               :10
## right hemisphere                                              :10
## coded as nirs but this is an fMRI experiment                  : 6
## channel 21 (significant for all sounds vs. silence comparison): 4
## individual data available                                     : 3
## (Other)                                                       :31
## NA's                                                          :26
```

```
##                                                                                    notes.stats
##  Mean and SD are plotted on figure 3.                                                    : 5
##  mean is beta                                                                            : 4
##  one-sided t-test: significant activation of the cortical region                         : 4
##  main effect of sound condition, F(4,14)                                                 : 3
##  mean and SD for each age group and sound type are available on fig. 2 (bar plot): 3
##  (Other)                                                                                 : 3
##  NA's                                                                                    :68
##       x_1                 x_2               SD_1              SD_2
##  Min.   : 0.00300   Min.   : 0.000   Min.   :0.00400   Min.   :0.0040
##  1st Qu.: 0.02222   1st Qu.: 0.018   1st Qu.:0.02175   1st Qu.:0.0170
##  Median : 0.38650   Median : 0.314   Median :0.07500   Median :0.0787
##  Mean   : 7.04624   Mean   : 6.221   Mean   :1.67802   Mean   :1.5919
##  3rd Qu.:11.77500   3rd Qu.: 9.550   3rd Qu.:3.35250   3rd Qu.:2.7000
##  Max.   :73.00000   Max.   :76.910   Max.   :9.50000   Max.   :8.7000
##  NA's   :30         NA's   :31       NA's   :32        NA's   :33
##        t                F              F..1.n.          df.F.
##  Min.   :1.180   Min.   : 4.240   Min.   :1.700   4,14   : 3
##  1st Qu.:2.080   1st Qu.: 5.005   1st Qu.:2.765   4,27   : 3
##  Median :2.260   Median : 6.930   Median :3.100   2,26   : 1
##  Mean   :2.312   Mean   : 7.326   Mean   :3.088   3,66   : 1
##  3rd Qu.:2.670   3rd Qu.: 8.610   3rd Qu.:3.285   3,72   : 1
##  Max.   :3.230   Max.   :12.880   Max.   :4.870   (Other): 2
##  NA's   :61      NA's   :83       NA's   :79      NA's   :79
##        d           corr
##  Min.   :0.48   Mode:logical
##  1st Qu.:0.48   NA's:90
##  Median :0.48
##  Mean   :0.48
##  3rd Qu.:0.48
##  Max.   :0.48
##  NA's   :89
```

```
#unique studies
papers <- levels(factor(DB$short_cite))
paste('A total of', length(papers), 'papers were included.')
```

```
## [1] "A total of 24 papers were included."
```

```
#number of unique infants
DB$n<-rowSums( cbind (DB$n_1,DB$n_2), na.rm=TRUE)
temp<-aggregate(n~same_infant,DB,mean)
paste('A total of', round(sum(temp$n)), 'infants contributed to the analysis')
```

```
## [1] "A total of 862 infants contributed to the analysis"
```

```
summary(DB$mean_age_1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.460   1.879  94.530  90.004 149.010 380.500
```

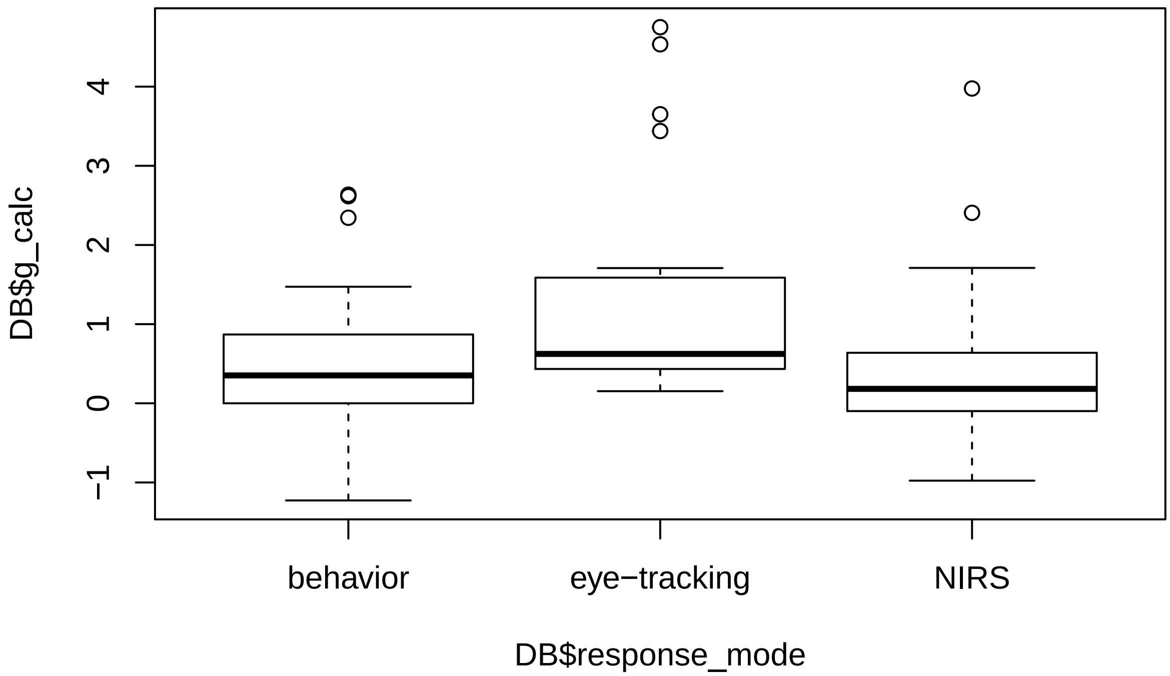
```
We coded the familiarity with the language used (native/foreign), the naturalness of the contrastive sou
```

Including Plots

```
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'),
        legend.position='none')
```

Sho: We assess significance of predictor variables by model comparison. To this end, we first create a base model, including moderators that influence ES apart from target moderators. This base model includes - infant age We include random effects of paper (study_ID), and random effects for independent infants within paper (same_infant). We use method="ML", which is appropriate for model comparison

```
#setting up of predictors
#http://stats.idre.ucla.edu/r/library/r-library-contrast-coding-systems-for-categorical-variables/

 #check that the experimental method doesn't make a difference (i.e. eye-tracking vs NIRS vs behavior)
#deviation coding: each level is compared to the overall mean of the dependent variable, intercept corr
contrasts(DB$response_mode) = contr.sum(length(levels(DB$response_mode)))
 #check that the language doesn't make a difference (true speech preference and not pref for native lan
#dummy coding: each level is compared to the reference level (native), the intercept corresponds to the
contrasts(DB$test_lang) <- contr.treatment(length(levels(DB$test_lang)))

 #moderators of interest
contrasts(DB$naturalness) <- contr.sum(length(levels(DB$naturalness)))

DB$species<-factor(DB$species)
contrasts(DB$species) <- contr.sum(length(levels(DB$species)))

DB$social<-factor(DB$social)
contrasts(DB$social) <- contr.sum(length(levels(DB$social)))

#fit models
 #check that the method used doesn't make a difference
plot(DB$g_calc~DB$response_mode)
```




```
tapply(DB$g_calc,DB$response_mode, mean,na.rm=T)
```

```
##     behavior eye-tracking         NIRS
##    0.5810529    1.2734347    0.4486749
```

```
tapply(DB$g_calc,DB$response_mode, sd,na.rm=T)
```

```
##     behavior eye-tracking         NIRS
##     1.064046     1.433764     1.006555
```

```
base_model <-rma.mv(g_calc, g_var_calc, mods = ~method, random = ~ 1 | study_ID/same_infant, data=DB, we

 #age varies with method (nirs<behavior<eye tracking)
tapply(DB$mean_age_1,DB$response_mode,mean,na.rm=T)
```

```
##     behavior eye-tracking         NIRS
##     85.09787    139.58534     53.91000
```

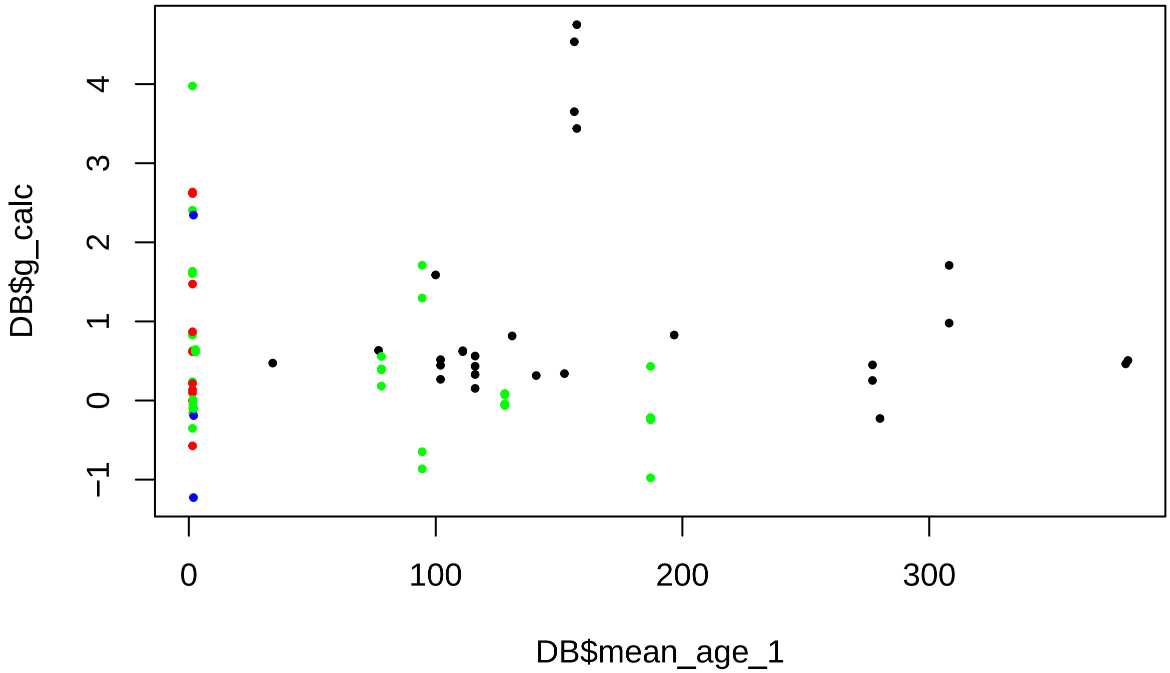
```
#Maybe response_mode is not the right variable for this.
table(DB$method,DB$response_mode)
```

```
##
##       behavior eye-tracking NIRS
##   CF         5           31    0
##   HAS        4            0    0
##   HPP       10            0    0
##   PL         0            0   40
```

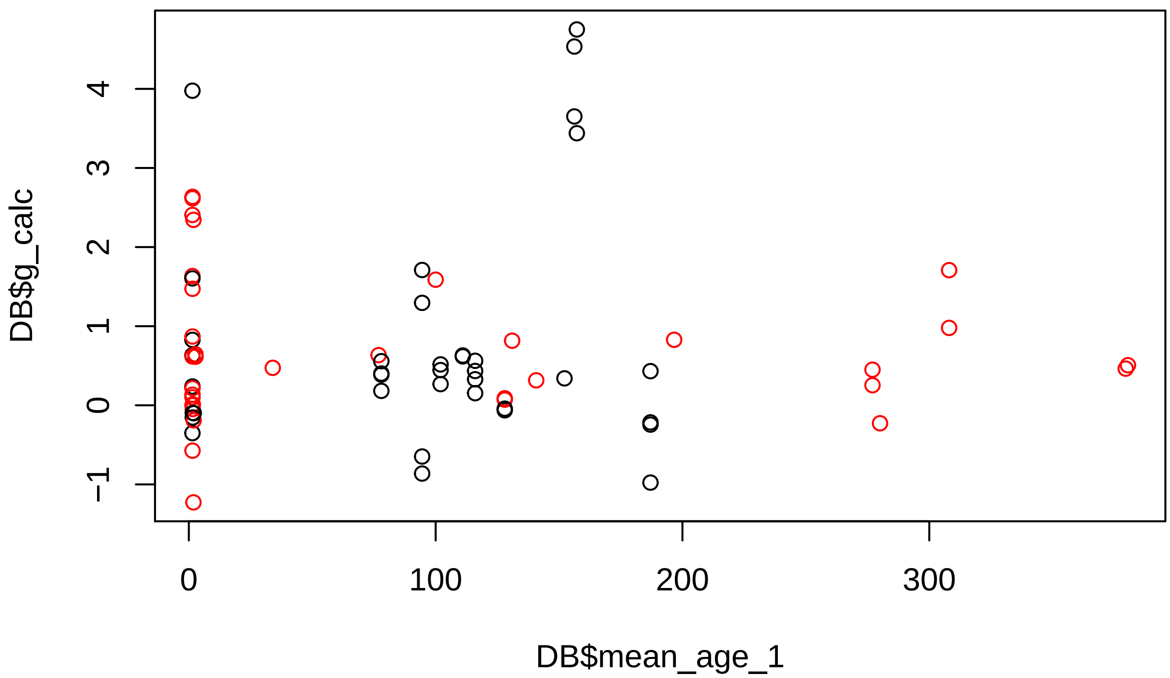
```
#plot g as a function of method
mycols=c("black","blue","red","green")
names(mycols)<-levels(DB$method)
mycols
```

```
##      CF     HAS     HPP      PL
## "black"  "blue"   "red" "green"
```

```r
plot(DB$g_calc~DB$mean_age_1,col=mycols[DB$method],pch=20,cex=.7)
```




```r
 #check also for test_lang (nativeness)
 #The language used for the speech trials doesn't make a difference
plot(DB$g_calc~DB$mean_age_1,col=DB$test_lang)
```




```r
tapply(DB$g_calc,DB$test_lang, mean,na.rm=T)
```

```
##    foreign    native
## 0.7880845 0.6830680
```

```r
tapply(DB$g_calc,DB$test_lang, sd,na.rm=T)
```

```
##   foreign    native
## 1.4410558 0.9079137
```

```r
base_model2 <-rma.mv(g_calc, g_var_calc, mods = ~ test_lang, random = ~ 1 | study_ID/same_infant, data=I

 #full model (with moderators of interest). As species and social are not orthogonal to naturalness, we
full_model <-rma.mv(g_calc, g_var_calc, mods= ~ naturalness, random = ~ 1 | study_ID/same_infant, data=I

summary(full_model)
```

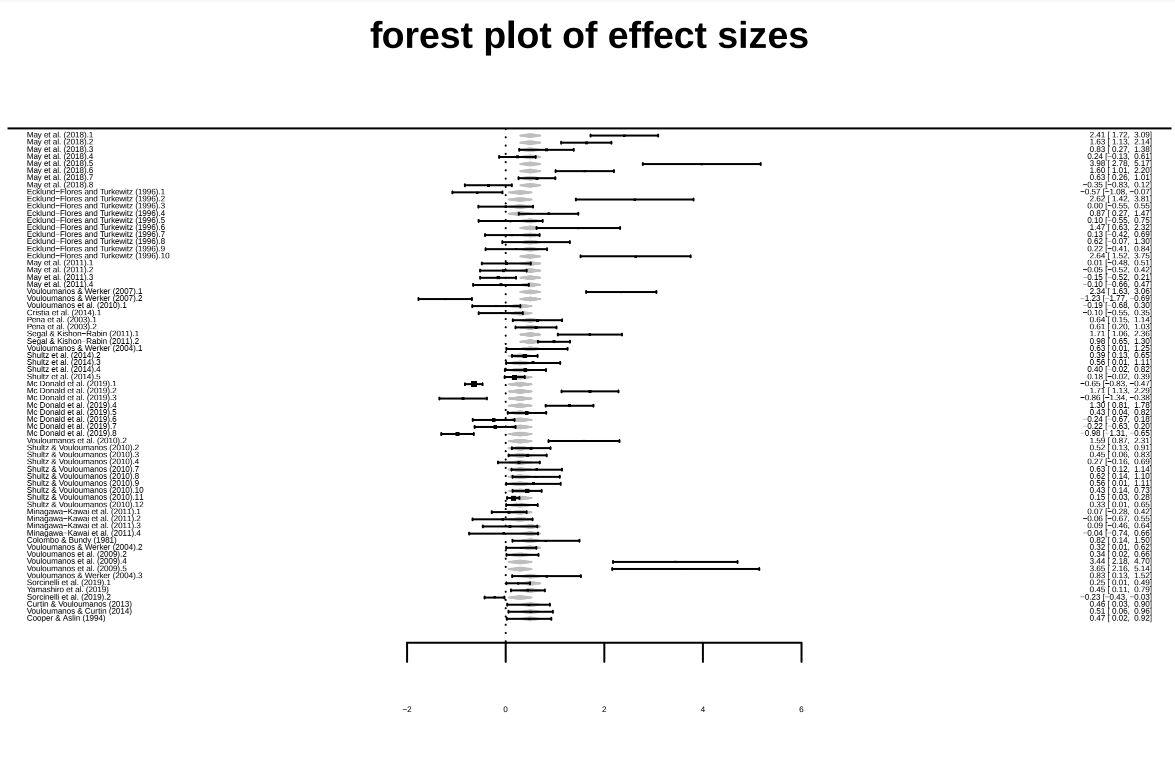
```
##
## Multivariate Meta-Analysis Model (k = 69; method: ML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -202.6722   471.9859   413.3444   422.2808   413.9694
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.0515  0.2270     20     no             study_ID
## sigma^2.2  0.0984  0.3137     35     no  study_ID/same_infant
##
## Test for Residual Heterogeneity:
## QE(df = 67) = 590.6695, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 2.1064, p-val = 0.1467
##
## Model Results:
##
##               estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt         0.3960  0.0857  4.6225  <.0001   0.2281  0.5640  ***
## naturalness1    0.1024  0.0706  1.4513  0.1467  -0.0359  0.2407
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#subset to natural sounds, as naturalness doesn't make a difference. This allows to test species and so
natural_only <-rma.mv(g_calc, g_var_calc, mods=~ species2*social2*agec, random = ~ 1 | study_ID/same_in


summary(natural_only)
```

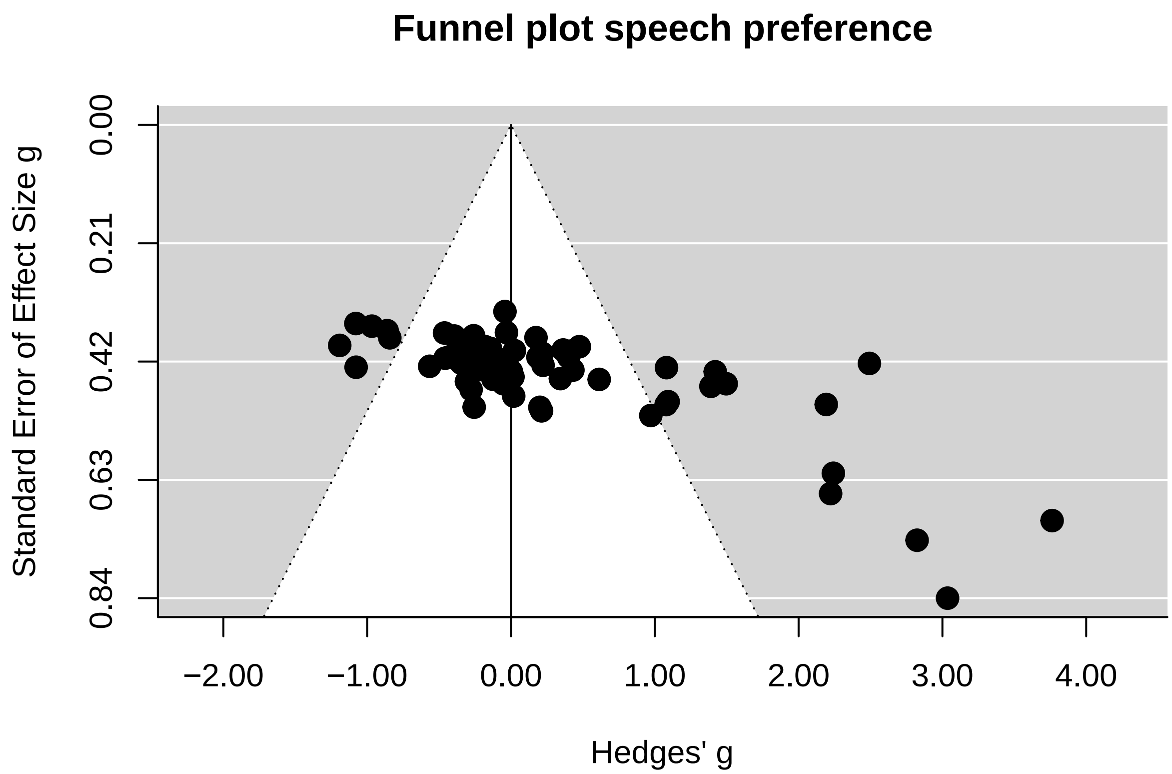
```
##
## Multivariate Meta-Analysis Model (k = 29; method: ML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -89.6201  209.6319  195.2401  206.1785  202.4401
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed               factor
## sigma^2.1  0.1851  0.4302      9     no             study_ID
```

```
## sigma^2.2  0.7389  0.8596     14     no  study_ID/same_infant
##
## Test for Residual Heterogeneity:
## QE(df = 23) = 278.7006, p-val < .0001
##
## Test of Moderators (coefficient(s) 2:6):
## QM(df = 5) = 21.0806, p-val = 0.0008
##
## Model Results:
##
##                              estimate      se     zval    pval    ci.lb
## intrcpt                        0.2556  0.3190   0.8012  0.4230  -0.3696
## species2heterospecific        -0.0675  0.1880  -0.3590  0.7196  -0.4359
## social2yes                     0.2375  0.1115   2.1306  0.0331   0.0190
## agec                           0.0049  0.0017   2.8308  0.0046   0.0015
## species2heterospecific:agec    0.0071  0.0047   1.5220  0.1280  -0.0020
## social2yes:agec               -0.0100  0.0022  -4.5341  <.0001  -0.0143
##                                ci.ub
## intrcpt                       0.8808
## species2heterospecific        0.3009
## social2yes                    0.4559    *
## agec                          0.0083   **
## species2heterospecific:agec   0.0163
## social2yes:agec              -0.0057  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
forest.rma(full_model, main = 'forest plot of effect sizes', xlab = 'Hedges\' g')
```



```
fun.fig <- funnel(base_model, cex=1.5, xlab='Hedges\' g', ylab="Standard Error of Effect Size g", digits
```




```
#Figure
pdf("Fig1.pdf")
par(mfrow=c(1,2)) #graphical parameters: A vector of the form c(nr, nc). Subsequent figures will be dra

funnel(base_model,cex=1.5,xlab='Hedge\'s g', ylab="Standard Error of Effect Size g", digits=2, main="Fu
dev.off()
```

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

```
#add symmetrize

# testing for asymetry (indicates a publication bias)
regtest(DB$g_calc,DB$g_var_calc)
```

```
##
## Regression Test for Funnel Plot Asymmetry
##
## model:     mixed-effects meta-regression model
## predictor: standard error
##
## test for funnel plot asymmetry: z = 9.4240, p < .0001
```

```
ranktest(DB$g_calc,DB$g_var_calc)
```

```
##
## Rank Correlation Test for Funnel Plot Asymmetry
##
## Kendall's tau = 0.3586, p < .0001
```

```
#calculate regression weight of studies that were conducted by supporters of NRV model #ALEX commented
# DB.periph<-DB[DB$periph==T,]
# DB.periph$weight<-1/sqrt(DB.periph$g_var_calc^2)
# DB.periph$forNRV<-0
# DB.periph$forNRV[DB.periph$study_ID=="Polka1996"|DB.periph$study_ID=="Polka2011"]<-1
# forNRV.weight<-sum(DB.periph$weight[DB.periph$forNRV==1])/sum(DB.periph$weight)
# forNRV.weight
```