

# A meta-analysis of mental rotation ability in the first years of life

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Commit ec3e55c

## Introduction

```
## [1] 32
## [1] 1776
## [1] 3.690371
## [1] 16.82184
## [1] 7.171171
gender %>%
  mutate(
    experiment = str_c(year, article, group, seq = ", "),
    # Convert mean sample age from days to months and center
    age_months = age_mean / 30.417,
    age_months_c = age_months - mean(age_months, na.rm = TRUE),
    # Add d_z from paired t test of condition means (Rosenthal, 1991)
    d_s_t = t * sqrt(1 / female_n + 1 / male_n),
    # Add d_z from ANOVA F value via conversion to a t value
    d_s_f = sqrt(as.numeric(f)) * sqrt(1 / female_n + 1 / male_n),
    # Add d_z from mean and standard deviation of the difference
    d_s_diff = (mean_diff_males_mean - mean_diff_females_mean) / sqrt(((male_n - 1) * (mean_diff_males_
    # Add d_av from mean difference and standard deviations (assumes r = 0.5)
    # (Cumming, 2012)
    # Add d from one-sample t test of novelty preference scores
    d_s_nov_pref = (novelty_pref_males_mean - novelty_pref_females_mean) / sqrt(((male_n - 1) * (novelty

    # Choose one type of outcome variable for each experiment
    di = case_when(
      # 1. If d was reported directed
      !is.na(d) ~ d,
      # 2. If a paired sample t test was reported
      !is.na(d_s_t) ~ d_s_t,
      # 3. If ANOVA was reported
      !is.na(d_s_f) ~ d_s_f,
      # 4. If the difference between means and its SD were reported
      !is.na(d_s_diff) ~ d_s_diff,
      # 6. If a novelty preference score and its SD were reported
      !is.na(d_s_nov_pref) ~ d_s_nov_pref
    ),
    # Keep track which type of outcome measure was chosen for each article
    di_type = case_when(
```

```

# 1. If d was reported directly
!is.na(d) ~ "d",
# 2. If a paired sample t test was reported
!is.na(d_s_t) ~ "d_s_t",
# 3. If ANOVA was reported
!is.na(d_s_f) ~ "d_s_f",
# 4. If the difference between means and its SD were reported
!is.na(d_s_diff) ~ "d_s_diff",
# 6. If a novelty preference score and its SD were reported
!is.na(d_s_nov_pref) ~ "d_s_nov_pref"
) %>%
  factor(levels = c("d", "d_s_t", "d_s_f", "d_s_diff", "d_s_nov_pref")),
# As per Lankens et. al. 2013, the formula for Hedge's is as follows, is this even correct? Can we
#  $g = d_i * (1 - (3 / (4 * (female_n + male_n) - 9)))$ ,
# Apply small sample correction using Hedges' exact method
# See http://dx.doi.org/10.20982/tqmp.14.4.p242
df = (male_n + female_n - 2),
j = exp(lgamma(df / 2) - log(sqrt(df / 2)) - lgamma((df - 1) / 2)),
gi = di * j,
# Compute empirical correlation based on sd_z and condition SDs
d_s = case_when(
  !is.na(d_s_t) ~ d_s_t,
  !is.na(d_s_f) ~ d_s_f,
  !is.na(d_s_diff) ~ d_s_diff,
  !is.na(d_s_nov_pref) ~ d_s_nov_pref
),
# harmonic mean of the sample sizes has to be taken here
n_h = (female_n * male_n) / (female_n + male_n),
sei = sqrt((df * 2 * (1 + (gi^2 * n_h * 0.5))) / ((df - 2) * n_h) - (gi^2 / j^2))
) %>%
  arrange(experiment) -> dat

```

```

dat %>%
  select(
    article,
    group,
    group_long,
    experiment,
    gi,
    di,
    di_type,
    d,
    d_s_t,
    d_s_f,
    d_s_diff,
    sei
  ) %>%
  print(n = Inf)

```

```

## # A tibble: 32 x 12
##   article    group group_long experiment    gi    di di_type    d
##   <chr>      <chr> <chr>      <chr>      <dbl> <dbl> <fct>    <dbl>
## 1 Rochat & ~ Exp.~ Experimen~ "1996Roch~ 0      0    d_s_f    NA
## 2 Rochat & ~ Exp.~ Experimen~ "1996Roch~ 0      0    d_s_f    NA

```

```
## 3 Hespos & ~ Exp.~ Experimen~ "1997Hesp~ 0      0      d_s_f  NA
## 4 Hespos & ~ Exp.~ Experimen~ "1997Hesp~ 0      0      d_s_f  NA
## 5 Hespos & ~ Exp.~ Experimen~ "1997Hesp~ 0      0      d_s_f  NA
## 6 Hespos & ~ Exp.~ Experimen~ "1997Hesp~ 0      0      d_s_f  NA
## 7 Hespos & ~ Exp.~ Experimen~ "1997Hesp~ 0      0      d_s_f  NA
## 8 Hespos & ~ Exp.~ Experimen~ "1997Hesp~ 0      0      d_s_f  NA
## 9 Moore & J~ All   Full samp~ "2008Moor~ 0.647  0.66  d      0.66
## 10 Quinn & L~ All   Full samp~ "2008Quin~ 1.28   1.32  d_s_t  NA
## 11 Moore & J~ All   Full samp~ "2011Moor~ 0.797  0.813 d_s_f  NA
## 12 Frick & M~ All   Full samp~ "2013Fric~ 0.472  0.482 d_s_f  NA
## 13 Möhring &~ All   Full samp~ "2013Möhr~ NA      NA    <NA>  NA
## 14 Schwarzer~ All   Full samp~ "2013Schw~ 0      0      d_s_f  NA
## 15 Schwarzer~ All   Full samp~ "2013Schw~ NA      NA    <NA>  NA
## 16 Frick & W~ Exp.~ Experimen~ "2014Fric~ 0      0      d_s_f  NA
## 17 Frick & W~ Exp.~ Experimen~ "2014Fric~ 0      0      d_s_f  NA
## 18 Frick & W~ Exp.~ Experimen~ "2014Fric~ 0      0      d_s_f  NA
## 19 Quinn & L~ Exp.~ Experimen~ "2014Quin~ 1.21   1.23  d_s_f  NA
## 20 Erdmann 2~ 5 mo. 5-months~ "2015Erdm~ 0.00996 0.01  d      0.01
## 21 Erdmann 2~ 9 mo. 9-months~ "2015Erdm~ 0.0299 0.03  d      0.03
## 22 Lauer et ~ All   Full samp~ "2015Laue~ 0.537  0.545 d_s_f  NA
## 23 Antrilli ~ All   Full samp~ "2016Antr~ 0      0      d_s_f  NA
## 24 Christodo~ All   Full samp~ "2016Chri~ 0      0      d_s_f  NA
## 25 Constanti~ All   Full samp~ "2016Cons~ 0.631  0.64  d      0.64
## 26 Gerhard &~ All   Full samp~ "2018Gerh~ 0      0      d_s_f  NA
## 27 Slone et ~ All   Full samp~ "2018Slon~ 0      0      d_s_f  NA
## 28 Kaaz & He~ Exp.~ Experimen~ "2020Kaaz~ 0.0199 0.02  d      0.02
## 29 Kaaz & He~ Exp.~ Experimen~ "2020Kaaz~ 0.446  0.45  d      0.45
## 30 Gerhard-S~ All   Full samp~ "2021Gerh~ 0      0      d_s_f  NA
## 31 Kelch et ~ Exp.~ Experimen~ "2021Kelc~ 0.425  0.440 d_s_f  NA
## 32 Kelch et ~ Exp.~ Experimen~ "2021Kelc~ NA      NA    <NA>  NA
## # ... with 4 more variables: d_s_t <dbl>, d_s_f <dbl>, d_s_diff <dbl>,
## #   sei <dbl>
```

```
dat$sei
```

```
## [1] 0.5560256 0.7032108 0.8976553 0.6592727 0.6995670 0.7319251
## [7] 0.6741999 0.7032108 0.4660499 0.6410455 0.4694193 0.4629853
## [13]      NA 0.4188805      NA 0.5621141 0.5695794 0.5621141
## [19] 0.4377461 0.1970758 0.2195507 0.3888732 0.5185630 0.4174236
## [25] 0.3979975 0.3299480 0.3203616 0.1672546 0.2936809 0.4574746
## [31] 0.6292969      NA
```

```
dat %>%
  mutate(
    ni = sample_size,
    vi = sei^2
  ) %>%
  filter(!is.na(gi)) %>%
  select(
    article, group, experiment, gi, ni, vi, sei, age_mean, age_sd, age_months_c, female_n, sample_size,
  ) %>%
  arrange(experiment) -> dat_r

# Three-level model
res_ml <- rma.mv(
```

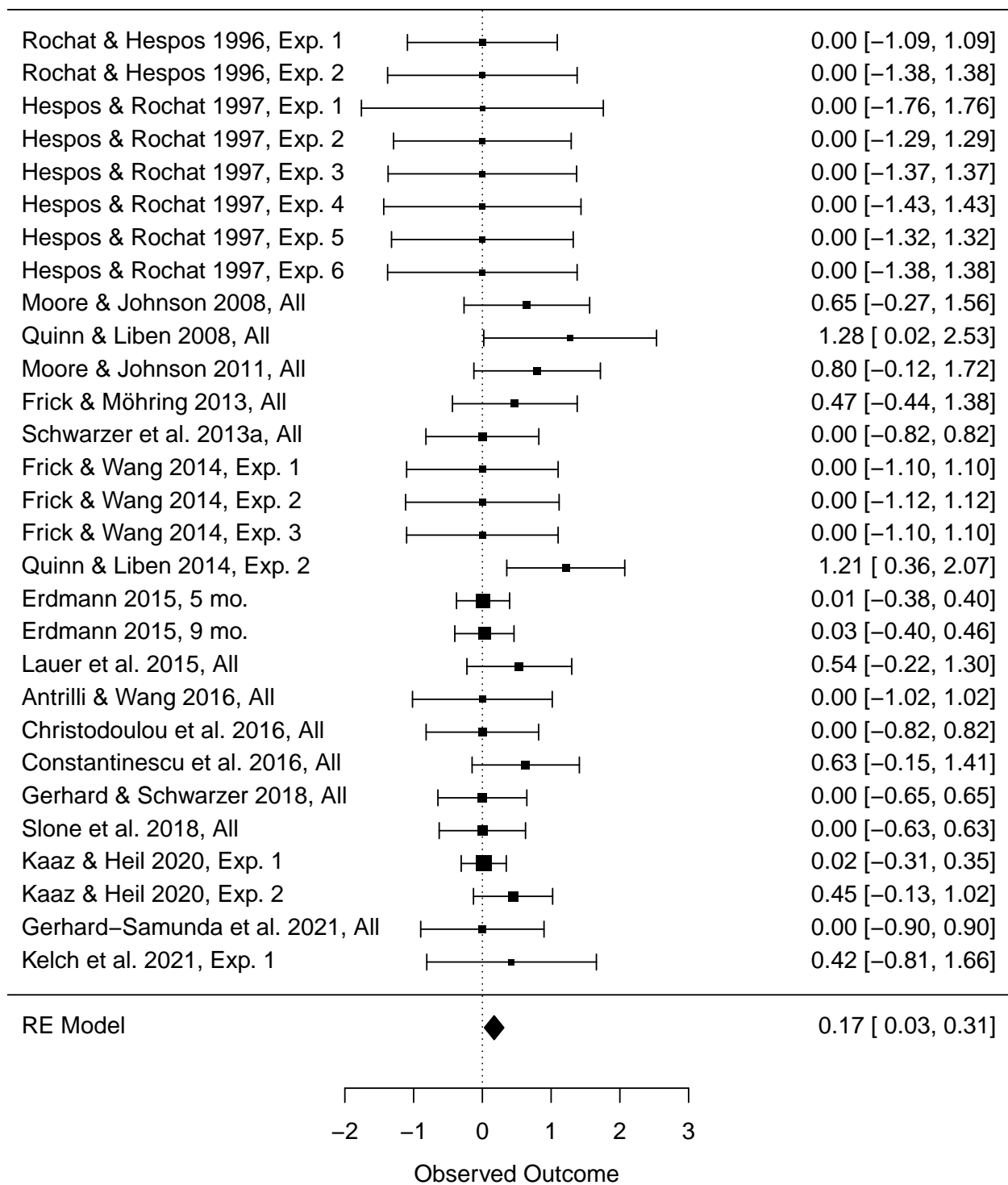
```

gi, vi,
random = ~ 1 | article / experiment,
data = dat_r,
slab = paste(article, group, sep = ", ")
)
print(res_ml)

##
## Multivariate Meta-Analysis Model (k = 29; method: REML)
##
## Variance Components:
##
##          estim      sqrt  nlvls  fixed          factor
## sigma^2.1  0.0000  0.0000    19    no          article
## sigma^2.2  0.0000  0.0000    29    no  article/experiment
##
## Test for Heterogeneity:
## Q(df = 28) = 18.9538, p-val = 0.8996
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##  0.1715  0.0714  2.4009  0.0164  0.0315  0.3115  *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# jpeg("forest_between_three_level.jpg")
forest(res_ml)

```



```
# (i2 <- dmetar::var.comp(res_ml))
# plot(i2)

# Check share of variance at each level of the model
round(res_ml$sigma2[1] / sum(res_ml$sigma2), 3) # Between-article (ICC)
```

```
## [1] 0.914
```



[illegible]







[illegible]





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finished in 4.7 seconds. Chain 1 Iteration: 19300 / 20000 [ 96%] (Sampling) Chain 1 Iteration: 19400 / 20000  
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4 Iteration: 19600 / 20000 [ 98%] (Sampling) Chain 4 Iteration: 19700 / 20000 [ 98%] (Sampling) Chain 4  
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Iteration: 20000 / 20000 [100%] (Sampling) Chain 4 finished in 5.0 seconds.

All 4 chains finished successfully. Mean chain execution time: 4.8 seconds. Total execution time: 5.1 seconds.

```
summary(res_prior)
```

Family: gaussian Links: mu = identity; sigma = identity Formula: gi | se(sei) ~ 0 + Intercept + (1 | article/experiment) Data: dat\_r (Number of observations: 29) Draws: 4 chains, each with iter = 19000; warmup = 0; thin = 1; total post-warmup draws = 76000

Group-Level Effects: ~article (Number of levels: 19) Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS sd(Intercept) 2.35 86.91 0.01 7.64 1.00 122455 Tail\_ESS sd(Intercept) 41087

~article:experiment (Number of levels: 29) Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS sd(Intercept) 3.42 172.81 0.01 7.80 1.00 132752 Tail\_ESS sd(Intercept) 40984

Population-Level Effects: Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS Intercept 0.00 1.01 -1.97 1.96 1.00 151526 53423

Family Specific Parameters: Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS sigma 0.00 0.00 0.00 0.00 NA NA NA

Draws were sampled using sample(hmc). For each parameter, Bulk\_ESS and Tail\_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

```
# plot(res_prior)

# Run Bayesian multilevel model
res_brm <- update(res_prior, sample_prior = FALSE)
```

Running MCMC with 4 chains, at most 12 in parallel...

Chain 1 Iteration: 1 / 20000 [ 0%] (Warmup) Chain 1 Iteration: 100 / 20000 [ 0%] (Warmup) Chain 1 Iteration: 200 / 20000 [ 1%] (Warmup) Chain 1 Iteration: 300 / 20000 [ 1%] (Warmup) Chain 1 Iteration: 400 / 20000 [ 2%] (Warmup) Chain 1 Iteration: 500 / 20000 [ 2%] (Warmup) Chain 1 Iteration: 600 / 20000 [ 3%] (Warmup) Chain 2 Iteration: 1 / 20000 [ 0%] (Warmup) Chain 2 Iteration: 100 / 20000 [ 0%] (Warmup) Chain 2 Iteration: 200 / 20000 [ 1%] (Warmup) Chain 2 Iteration: 300 / 20000 [ 1%] (Warmup) Chain 2 Iteration: 400 / 20000 [ 2%] (Warmup) Chain 2 Iteration: 500 / 20000 [ 2%] (Warmup) Chain 3 Iteration: 1 / 20000 [ 0%] (Warmup) Chain 3 Iteration: 100 / 20000 [ 0%] (Warmup) Chain 3 Iteration: 200 / 20000 [ 1%] (Warmup) Chain 3 Iteration: 300 / 20000 [ 1%] (Warmup) Chain 3 Iteration: 400 / 20000 [ 2%] (Warmup) Chain 4 Iteration: 1 / 20000 [ 0%] (Warmup) Chain 4 Iteration: 100 / 20000 [ 0%] (Warmup) Chain 4 Iteration: 200 / 20000 [ 1%] (Warmup) Chain 4 Iteration: 300 / 20000 [ 1%] (Warmup) Chain 1 Iteration: 700 / 20000 [ 3%] (Warmup) Chain 1 Iteration: 800 / 20000 [ 4%] (Warmup) Chain 1 Iteration: 900 / 20000 [ 4%] (Warmup) Chain 1 Iteration: 1000 / 20000 [ 5%] (Warmup) Chain 1 Iteration: 1001 / 20000 [ 5%] (Sampling) Chain 1 Iteration: 1100 / 20000 [ 5%] (Sampling) Chain 1 Iteration: 1200 / 20000 [ 6%] (Sampling) Chain 2 Iteration: 600 / 20000 [ 3%] (Warmup) Chain 2 Iteration: 700 / 20000 [ 3%] (Warmup) Chain 2 Iteration: 800 / 20000 [ 4%] (Warmup) Chain 2 Iteration: 900 / 20000 [ 4%] (Warmup) Chain 2 Iteration: 1000 / 20000 [ 5%] (Warmup) Chain 2 Iteration: 1001 / 20000 [ 5%] (Sampling) Chain 2 Iteration: 1100 / 20000 [ 5%] (Sampling) Chain 2 Iteration: 1200 / 20000 [ 6%] (Sampling) Chain 3 Iteration: 500 / 20000 [ 2%] (Warmup) Chain 3 Iteration: 600 / 20000 [ 3%] (Warmup) Chain 3 Iteration: 700 / 20000 [ 3%] (Warmup) Chain 3 Iteration: 800 / 20000 [ 4%] (Warmup) Chain 3 Iteration: 900 / 20000 [ 4%] (Warmup) Chain 3 Iteration: 1000 / 20000 [ 5%] (Warmup) Chain 3 Iteration: 1001 / 20000 [ 5%] (Sampling) Chain 3 Iteration: 1100 / 20000 [ 5%] (Sampling) Chain 4 Iteration: 400 / 20000 [ 2%] (Warmup) Chain 4 Iteration: 500 / 20000 [ 2%] (Warmup) Chain 4 Iteration: 600 / 20000 [ 3%] (Warmup) Chain 4 Iteration: 700 / 20000 [ 3%] (Warmup) Chain 4 Iteration: 800 / 20000 [ 4%] (Warmup) Chain 4 Iteration: 900 / 20000 [ 4%] (Warmup) Chain 1 Iteration: 1300 / 20000 [ 6%] (Sampling) Chain 1 Iteration: 1400 / 20000 [ 7%] (Sampling) Chain 1 Iteration: 1500 / 20000 [ 7%] (Sampling) Chain 1 Iteration: 1600 / 20000 [ 8%] (Sampling) Chain 2 Iteration: 1300 / 20000 [ 6%] (Sampling) Chain 2 Iteration: 1400 / 20000 [ 7%] (Sampling) Chain 2 Iteration: 1500 / 20000 [ 7%] (Sampling) Chain 2 Iteration: 1600 / 20000 [ 8%] (Sampling) Chain 3 Iteration: 1200 / 20000 [ 6%] (Sampling) Chain 3 Iteration: 1300 / 20000 [ 6%] (Sampling) Chain 3 Iteration: 1400 / 20000 [ 7%] (Sampling) Chain 3 Iteration: 1500 / 20000 [ 7%] (Sampling) Chain 4 Iteration: 1000 / 20000 [ 5%] (Warmup) Chain 4 Iteration: 1001 / 20000 [ 5%] (Sampling) Chain 4 Iteration: 1100 / 20000 [ 5%] (Sampling) Chain 4 Iteration: 1200 / 20000 [ 6%] (Sampling) Chain 4 Iteration: 1300 / 20000 [ 6%] (Sampling) Chain 1 Iteration: 1700 / 20000 [ 8%] (Sampling) Chain 1 Iteration: 1800 / 20000 [ 9%] (Sampling) Chain 1 Iteration: 1900 / 20000 [ 9%] (Sampling) Chain 1 Iteration: 2000 / 20000 [ 10%] (Sampling) Chain 2 Iteration: 1700 / 20000 [ 8%] (Sampling) Chain 2 Iteration: 1800 / 20000 [ 9%] (Sampling) Chain 2 Iteration: 1900 / 20000 [ 9%] (Sampling) Chain 2 Iteration: 2000 / 20000 [ 10%] (Sampling) Chain 3 Iteration: 1600 /

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 (Sampling) Chain 4 Iteration: 18800 / 20000 [ 94%] (Sampling) Chain 4 Iteration: 18900 / 20000 [ 94%]  
 (Sampling) Chain 4 Iteration: 19000 / 20000 [ 95%] (Sampling) Chain 1 Iteration: 19700 / 20000 [ 98%]  
 (Sampling) Chain 1 Iteration: 19800 / 20000 [ 99%] (Sampling) Chain 1 Iteration: 19900 / 20000 [ 99%]  
 (Sampling) Chain 2 Iteration: 19300 / 20000 [ 96%] (Sampling) Chain 2 Iteration: 19400 / 20000 [ 97%]  
 (Sampling) Chain 2 Iteration: 19500 / 20000 [ 97%] (Sampling) Chain 3 Iteration: 19700 / 20000 [ 98%]  
 (Sampling) Chain 3 Iteration: 19800 / 20000 [ 99%] (Sampling) Chain 4 Iteration: 19100 / 20000 [ 95%]  
 (Sampling) Chain 4 Iteration: 19200 / 20000 [ 96%] (Sampling) Chain 1 Iteration: 20000 / 20000 [100%]  
 (Sampling) Chain 2 Iteration: 19600 / 20000 [ 98%] (Sampling) Chain 2 Iteration: 19700 / 20000 [ 98%]  
 (Sampling) Chain 3 Iteration: 19900 / 20000 [ 99%] (Sampling) Chain 3 Iteration: 20000 / 20000 [100%]  
 (Sampling) Chain 4 Iteration: 19300 / 20000 [ 96%] (Sampling) Chain 4 Iteration: 19400 / 20000 [ 97%]  
 (Sampling) Chain 1 finished in 5.6 seconds. Chain 3 finished in 5.5 seconds. Chain 2 Iteration: 19800 /  
 20000 [ 99%] (Sampling) Chain 2 Iteration: 19900 / 20000 [ 99%] (Sampling) Chain 2 Iteration: 20000 /  
 20000 [100%] (Sampling) Chain 4 Iteration: 19500 / 20000 [ 97%] (Sampling) Chain 4 Iteration: 19600 /  
 20000 [ 98%] (Sampling) Chain 4 Iteration: 19700 / 20000 [ 98%] (Sampling) Chain 2 finished in 5.7 seconds.  
 Chain 4 Iteration: 19800 / 20000 [ 99%] (Sampling) Chain 4 Iteration: 19900 / 20000 [ 99%] (Sampling)  
 Chain 4 Iteration: 20000 / 20000 [100%] (Sampling) Chain 4 finished in 5.8 seconds.

All 4 chains finished successfully. Mean chain execution time: 5.6 seconds. Total execution time: 5.9 seconds.

```
summary(res_brm)
```

```
## Warning: There were 2 divergent transitions after warmup.
## Increasing adapt_delta above may help. See http://mc-stan.org/misc/
## warnings.html#divergent-transitions-after-warmup
```

Family: gaussian Links: mu = identity; sigma = identity Formula: gi | se(sei) ~ 0 + Intercept + (1 | article/experiment) Data: dat\_r (Number of observations: 29) Draws: 4 chains, each with iter = 19000; warmup = 0; thin = 1; total post-warmup draws = 76000

Group-Level Effects: ~article (Number of levels: 19) Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS  
sd(Intercept) 0.11 0.09 0.00 0.32 1.00 37393 Tail\_ESS sd(Intercept) 35807

~article:experiment (Number of levels: 29) Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS  
sd(Intercept) 0.10 0.07 0.00 0.28 1.00 42582 Tail\_ESS sd(Intercept) 36607

Population-Level Effects: Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS Intercept 0.20  
0.09 0.03 0.39 1.00 72093 49365

Family Specific Parameters: Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS sigma 0.00  
0.00 0.00 0.00 NA NA NA

Draws were sampled using sample(hmc). For each parameter, Bulk\_ESS and Tail\_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

```
# Compute probabilities of the meta-analytic being greater than 0
# hypothesis(res_brm, "Intercept > 0")$hypothesis
# Summarise fixed effects (incl. Bayes factors)
describe_posterior(
  res_brm,
  centrality = "mean", ci = 0.95, ci_method = "ETI",
  test = c("p_direction", "rope", "bayesfactor"),
  rope_range = c(-0.1, 0.1)
)
```

Summary of Posterior Distribution

**Parameter | Mean | 95% CI | pd | ROPE | % in ROPE | Rhat | ESS | BF**

(Intercept) | 0.20 | [0.03, 0.39] | 98.93% | [-0.10, 0.10] | 10.94% | 1.000 | 69426.00 | 1.29

```
# Compute by-experiment variance
var_experiment <- as.matrix(
  res_brm,
  variable = "sd_article:experiment__Intercept"
)^2
mean_qi(var_experiment)
```

	y	ymin	ymax	.width	.point	.interval
1	0.01487582	1.498386e-05	0.07569403	0.95	mean	qi

```
# Compute by-article variance
var_article <- as.matrix(
  res_brm,
  variable = "sd_article__Intercept"
)^2
mean_qi(var_article)
```

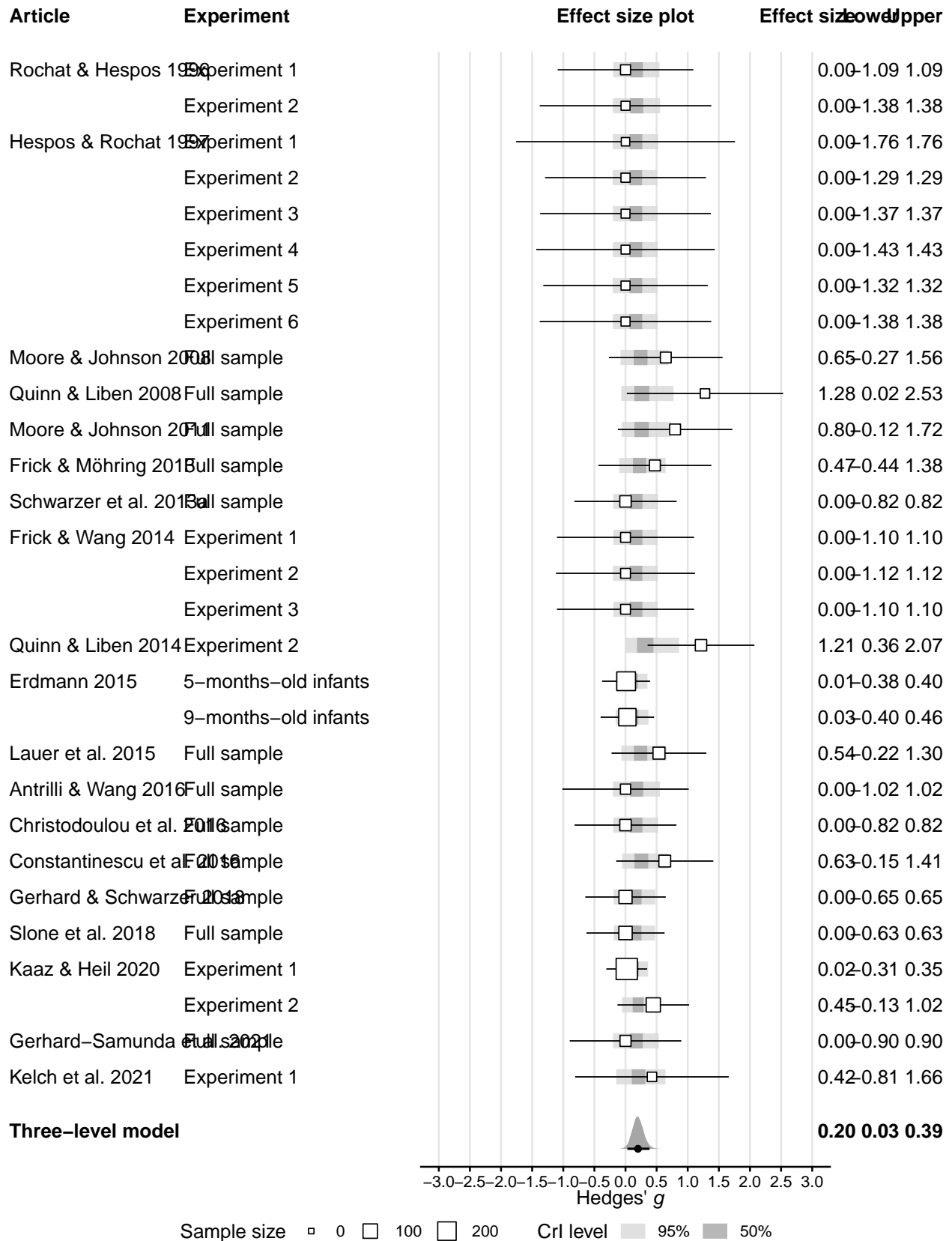
	y	ymin	ymax	.width	.point	.interval
1	0.01938775	1.71046e-05	0.1030046	0.95	mean	qi

```
# Compute intra-class correlation
var_total <- (var_experiment + var_article)
icc_draws <- var_article / var_total
mean_qi(icc_draws)
```

	y	ymin	ymax	.width	.point	.interval
1	0.5265618	0.001898055	0.9987187	0.95	mean	qi

```
## Warning: There were 2 divergent transitions after warmup.  
## Increasing adapt_delta above may help. See http://mc-stan.org/misc/  
## warnings.html#divergent-transitions-after-warmup
```

```
## Warning: There were 2 divergent transitions after warmup.  
## Increasing adapt_delta above may help. See http://mc-stan.org/misc/  
## warnings.html#divergent-transitions-after-warmup
```





```

# Prior sensitivity analysis
list(
  "Intercept U(-10,10)" = c(
    set_prior("uniform(-10, 10)", class = "Intercept"),
    set_prior("cauchy(0, 0.3)", class = "sd")
  ),
  "Intercept N(0,0.2)" = c(
    set_prior("normal(0, 0.2)", class = "Intercept"),
    set_prior("cauchy(0, 0.3)", class = "sd")
  ),
  "SD U(0,10)" = c(
    set_prior("normal(0, 1)", class = "Intercept"),
    set_prior("uniform(0, 10)", class = "sd")
  ),
  "SD Student-t(10,0,0.2)" = c(
    set_prior("normal(0, 1)", class = "Intercept"),
    set_prior("student_t(10, 0, 0.2)", class = "sd")
  )
) %>%
  # Re-run the meta-analysis with different priors
  map(
    function(prior_sens) update(res_brm, prior = prior_sens, refresh = 0)
  ) -> res_prior_sens

```

```
## Running MCMC with 4 chains, at most 12 in parallel...
```

```
##
```

```
## Chain 1 finished in 5.5 seconds.
```

```
## Chain 2 finished in 5.5 seconds.
```

```
## Chain 3 finished in 5.6 seconds.
```

```
## Chain 4 finished in 5.5 seconds.
```

```
##
```

```
## All 4 chains finished successfully.
```

```
## Mean chain execution time: 5.5 seconds.
```

```
## Total execution time: 5.7 seconds.
```

```
## Running MCMC with 4 chains, at most 12 in parallel...
```

```
##
```

```
## Chain 1 finished in 6.4 seconds.
```

```
## Chain 2 finished in 6.4 seconds.
```

```
## Chain 3 finished in 6.5 seconds.
```

```
## Chain 4 finished in 6.5 seconds.
```

```
##
```

```
## All 4 chains finished successfully.
```

```
## Mean chain execution time: 6.5 seconds.
```

```
## Total execution time: 6.8 seconds.
```

```
## Warning: It appears as if you have specified an upper bounded prior on a parameter that has no natural upper bound.
## If this is really what you want, please specify argument 'ub' of 'set_prior' appropriately.
```

```
## Warning occurred for prior
```

```
## sd ~ uniform(0, 10)
```

```
## Warning: It appears as if you have specified an upper bounded prior on a parameter that has no natural upper bound.
## If this is really what you want, please specify argument 'ub' of 'set_prior' appropriately.
```

```
## Warning occurred for prior
```

```
## sd ~ uniform(0, 10)
```



```
## warnings.html#divergent-transitions-after-warmup
## Warning: There were 11 divergent transitions after warmup.
## Increasing adapt_delta above may help. See http://mc-stan.org/misc/
## warnings.html#divergent-transitions-after-warmup

## Warning: There were 3 divergent transitions after warmup.
## Increasing adapt_delta above may help. See http://mc-stan.org/misc/
## warnings.html#divergent-transitions-after-warmup

## Warning: There were 7 divergent transitions after warmup.
## Increasing adapt_delta above may help. See http://mc-stan.org/misc/
## warnings.html#divergent-transitions-after-warmup

# Save the table
write_csv(tab_sens, file = here(tables_dir, "between_sensitivity_analysis.csv"))
```