

Supplemental Results

Risk of Bias Moderator Analyses

Allocation concealment: $Q\text{-}M = .89, df = 2, p = .64$

Incomplete outcome reporting: $Q\text{-}M = 3.0, df = 1, p = .08$

Selective outcome reporting: $Q\text{-}M = 1.72, df = 2, p = .42$

Sequence generation: $Q\text{-}M = 3.5, df = 1, p = .06$

Blinding of outcome assessors: $Q\text{-}M = 1.3, df = 2, p = .51$

Blinding of participants and personnel: $Q\text{-}M = 2.18, df = 2, p = .34$

Other sources of bias: $Q\text{-}M = 0.45, df = 1, p = .50$

Sensitivity Analyses

Outlier Removed

Multilevel Estimates

Acquisition: $g = .23, p = .10, 95\% \text{ CI } [-.04, .51]$

Immediate retention: $g = .12, p = .43, 95\% \text{ CI } [-.18, .41]$

Delayed retention: $g = .19, p = .10, 95\% \text{ CI } [-.04, .42]$

Categorical Moderator Analyses

Age: $Q\text{-}M = 5.42, df = 6, p = .49$

Skill: $Q\text{-}M = 1.1, df = 3, p = .78$

Faded: $Q\text{-}M = 2.17, df = 4, p = .70$

Yoked: $Q\text{-}M = 6.27, df = 4, p = .18$

Feedback: $Q\text{-}M = 7.64, df = 8, p = .47$

Measure: $Q\text{-}M = 30.65, df = 22, p = .10$

Measure without test interaction: $Q\text{-}M = 9.07, df = 8, p = .34$

Bandwidth: $Q\text{-}M = 3.35, df = 5, p = .65$

Mete-regression Analyses

Trials: $Q-M = 5.80, df = 3, p = .12$

Days: $Q-M = 2.72, df = 3, p = .44$

Frequency (overall analysis): $Q-M = 1.99, df = 3, p = .57$

Immediate retention interval: $Q-M = .087, df = 2, p = .65$

Test Time Moderators

Immediate retention vs. delayed retention: $Q-M = .24, df = 1, p = .63$.

Cluster Robust Inference Methods

Cluster Robust Multilevel Estimates

Acquisition: $g = .19, p = .20, 95\% \text{ CI } [-.11, .50]$

Immediate retention: $g = .14, p = .93, 95\% \text{ CI } [-.29, .31]$

Delayed retention $g = .19, p = .15, 95\% \text{ CI } [-.07, .46]$

Correlated and Hierarchical Effects (CHE) Model Estimates with Approximate V Matrix ($r = .7$)

Acquisition: $g = .19, p = .22, 95\% \text{ CI } [-.13, .51]$

Immediate retention: $g = .002, p = .99, 95\% \text{ CI } [-.34, .34]$

Delayed retention: $g = .20, p = .13, 95\% \text{ CI } [-.07, .48]$

Cluster Robust Multilevel Estimates with Outlier Removed

Acquisition: $g = .23, p = .11, 95\% \text{ CI } [-.06, .52]$

Immediate retention: $g = .12, p = .34, 95\% \text{ CI } [-.13, .37]$

Delayed retention $g = .19, p = .14, 95\% \text{ CI } [-.07, .45]$

CHE Model Estimates with Approximate V Matrix ($r = .7$) and Outlier Removed

Acquisition: $g = .23, p = .13, 95\% \text{ CI } [-.08, .53]$

Immediate retention: $g = .12, p = .36, 95\% \text{ CI } [-.15, .38]$

Delayed retention: $g = .20, p = .13, 95\% \text{ CI } [-.06, .46]$

Four Level Model: Measure Nested in Test Nested in Experiment

Multilevel Estimates

Acquisition: $g = .15, p = .13, 95\% \text{ CI } [-.04, .34]$

Immediate retention: $g = .07, p = .56, 95\% \text{ CI } [-.15, .29]$

Delayed retention: $g = .18, p = .051, 95\% \text{ CI } [-.001, .36]$

Four Level Model: Outlier Removed

Multilevel Estimates

Acquisition: $g = .18, p = .07, 95\% \text{ CI } [-.01, .37]$

Immediate retention: $g = .12, p = .27, 95\% \text{ CI } [-.09, .34]$

Delayed retention: $g = .18, p = .051, 95\% \text{ CI } [-.001, .36]$

Moderator Analyses

Age: $Q-M = 7.81, df = 6, p = .25$

Age (outlier removed): $Q-M = 6.06, df = 6, p = .42$

Skill: $Q-M = 1.75, df = 3, p = .63$

Skill (outlier removed): $Q-M = .98, df = 3, p = .81$

Task: $Q-M = 19.47, df = 8, p = .01$

Task (Drews et al. 2021 removed): $Q-M = 9.4, df = 8, p = .31$

Bandwidth: $Q-M = 1.74, df = 5, p = .88$

Bandwidth (outlier removed): $Q-M = 1.19, df = 5, p = .94$

Faded: $Q-M = 3.03, df = 5, p = .70$

Faded (outlier removed): $Q-M = 2.36, df = 5, p = .80$

Yoked: $Q-M = 6.49, df = 4, p = .17$

Yoked (outlier removed): $Q-M = 6.22, df = 4, p = .18$

Feedback: $Q-M = 11.66, df = 16, p = .77$

Feedback (outlier removed): $Q-M = 8.53, df = 16, p = .93$

Feedback (interaction removed): $Q-M = 4.15, df = 6, p = .66$

Feedback Collapsed: Spatial error, temporal error, variable error, movement time, form, and other.

Feedback: $Q-M = 11.41, df = 14, p = .78$

Feedback (outlier removed): $Q-M = 8.71, df = 14, p = .92$

Feedback (interaction removed): $Q-M = 2.21, df = 5, p = .82$

Feedback (delayed retention only): $Q-M = 2.07, df = 5, p = .84$

Measure: $Q-M = 16.17, df = 28, p = .96$

Measure (outlier removed): $Q-M = 14.49, df = 28, p = .98.$

Measure (interaction removed): $Q-M = 5.24, df = 10, p = .87.$

Do Measures Selected as Primary Differ from Secondary Measures

Full sample: $Q-M = 1.85, df = 5, p = .87$

Outlier removed: $Q-M = 1.08, df = 5, p = .96$

Meta-regression Analyses

Trials: $Q-M = 9.83, df = 5, p = .08$

Trials (outlier removed): $Q-M = 9.92, df = 5, p = .08$

Days: $Q-M = 7.75, df = 5, p = .17$

Days (outliers removed): $Q-M = 7.70, df = 5, p = .17$

Days: $Q-M = 7.75, df = 5, p = .17$

Univariate Analysis of Transfer Test Data

Estimate: $g = .15, p = .45, 95\% \text{ CI } [-.24, .55]$

Heterogeneity: $Q = 68.47, df = 14, p < .0001. \tau^2 = .57$

Estimate (outlier removed): $g = .05, p = .83, 95\% \text{ CI } [-.38, .48]$

Heterogeneity (outliers removed): $Q = 55.19, df = 13, p < .0001. \tau^2 = .42$

Moderator Analyses of Spatial Error Subset and Delayed Retention Time Point

Age: $Q-M = 1.72, df = 1, p = .19$

Skill: $Q-M = .61, df = 1, p = .44$

Task: $Q-M = 1.77, df = 2, p = .41$

Faded: $Q-M = .72, df = 1, p = .40$

Yoked: $Q-M = .29, df = 1, p = .59$

Feedback: $Q-M = 5.08, df = 4, p = .28$

Trials: $Q-M < .001$, $df = 1$, $p = .98$

Days: $Q-M = .002$, $df = 1$, $p = .96$

Frequency: $Q-M = 1.14$, $df = 1$, $p = .29$

Simulation Study

```
1. #####
2. #Meta-analysis of dependent effect sizes simulation #
3. #####
4. library(MBESS)
5. library(metafor)
6. library(faux)
7. library(tidyverse)
8. set.seed(1000)
9.
10.
11.
12. # individual meta-analysis simulation function
13.
14. onemeta <- function(nSims, cxa, exa, cxb, exb, rho, sample_lb, sample_ub){
15.   esd_1 <- numeric(nSims) #empty container for all simulated ES
16.   esd_2 <- numeric(nSims) #empty container for all simulated ES
17.   SSn1 <- numeric(nSims) #empty container for random sample sizes group 1
18.   SSn2 <- numeric(nSims) #empty container for random sample sizes group 2
19.   for(i in 1:nSims){ #for each simulated experiment
20.     SampleSize <- sample(sample_lb:sample_ub, 1) #randomly draw a sample between lb and ub
21.     ge <- rnorm_multi(n = SampleSize, 2, 0, 1, r = rho, varnames = c("t1", "t2")) #sample
        from a multivariate normal
22.     gc <- rnorm_multi(n = SampleSize, 2, 0, 1, r = rho, varnames = c("t1", "t2")) #sample
        from a multivariate normal
23.     gc$t1 <- gc$t1 + cxa # add effect to time 1 for control
24.     ge$t1 <- ge$t1 + exa # add effect to time 1 for experimental
25.     gc$t2 <- gc$t2 + cxb # add effect to time 2 for experimental
26.     ge$t2 <- ge$t2 + exb # add effect to time 2 for experimental
27.     SSn1[i] <- SampleSize #save sample size group 1
28.     SSn2[i] <- SampleSize #save sample size group 2
29.     esd_1[i] <- smd(Mean.1= mean(ge$t1), Mean.2=mean(gc$t1), s.1=sd(ge$t1), s.2=sd(gc$t1),
        n.1=SampleSize, n.2=SampleSize, Unbiased=TRUE) #Use MBESS to calc Hedges g
30.     esd_2[i] <- smd(Mean.1= mean(ge$t2), Mean.2=mean(gc$t2), s.1=sd(ge$t2), s.2=sd(gc$t2),
        n.1=SampleSize, n.2=SampleSize, Unbiased=TRUE)}
31.     #Insert effect sizes and sample sizes
32.     n1 <- c(SSn1)
33.     n2 <- c(SSn2)
34.     J <- 1-3/(4*( SSn1+ SSn2-2))-1) #correction for bias
35.     esdv_1 <- (((SSn1+SSn2)/(SSn1*SSn2))+((esd_1^2/(2*(SSn1+SSn2)))))*J^2
36.     esdv_2 <- (((SSn1+SSn2)/(SSn1*SSn2))+((esd_2^2/(2*(SSn1+SSn2)))))*J^2
37.     dat <- as.data.frame(cbind(esd_1, esdv_1, esd_2, esdv_2, n1, n2))
38.     dat$id <- seq.int(nrow(dat))
39.     dat <- dat %>%
40.       pivot_longer(
41.         cols = !c(n1,n2,id),
42.         names_to = c(".value", "num"),
43.         names_sep = "_"
44.       )
45.     return(as.data.frame(dat))
46.   }
```

```

47.
48.
49.
50. # simulation study ## multilevel models
51.
52. iters <- 100 #number of simulated meta-analyses
53. mpval <- rep(NA, iters) #empty container for moderator p-values
54. difb <- rep(NA, iters) #empty container for moderator beta values
55. nSims <- 32 #number of experiments per meta-analysis
56. cxa <- 0 #intervention effect for control group at first time point
57. exa <- 0 #intervention effect for experimental group at first time point
58. cxb <- 0 #intervention effect for control group at second time point
59. exb <- 0 #intervention effect for experimental group at second time point
60. rho <- .5 #correlation between time points in the population
61. sample_lb <- 10 #lower bound for number of participants per experiment
62. sample_ub <- 30 #upper bound for number of participants per experiment
63.
64.
65.
66.
67. for (i in 1:iters){
68.   dat <- onemeta(nSims = nSims, cxa = cxa, exa = exa, cxb = cxb, exb = exb, rho = rho,
69.     sample_lb = sample_lb, sample_ub = sample_ub)
70.   tryCatch(
71.     {
72.       res <- rma.mv(esd, esdv, mods = ~factor(num), random = ~1|id/num, data = dat) #fit
73.       mpval[i] <- res$QMp
74.       difb[i] <- res$b[2]},
75.     error=function(error_message) {
76.       message(error_message)
77.       return(NA) #when the model fails to converge, store as NA rather than stopping the
78.     }
79.   )
80.
81. mean(mpval <= .05, na.rm = TRUE) # mean rejection rate with alpha = .05
82. mean(difb, na.rm = TRUE) # mean estimate of difference in intervention effect between time
83.   points
84.
85.
86.
87.
88.
89. # simulation study ## cluster robust methods
90.
91. iters <- 100 #number of simulated meta-analyses
92. mpval <- rep(NA, iters) #empty container for moderator p-values
93. difb <- rep(NA, iters) #empty container for moderator beta values
94. nSims <- 32 #number of experiments per meta-analysis
95. cxa <- 0 #intervention effect for control group at first time point
96. exa <- 0 #intervention effect for experimental group at first time point
97. cxb <- 0 #intervention effect for control group at second time point
98. exb <- 0 #intervention effect for experimental group at second time point
99. rho <- .5 #correlation between time points in the population
100. sample_lb <- 10 #lower bound for number of participants per experiment
101. sample_ub <- 30 #upper bound for number of participants per experiment
102.
103.
104.
105. for (i in 1:iters){
106.   dat <- onemeta(nSims = nSims, cxa = cxa, exa = exa, cxb = cxb, exb = exb, rho = rho,
107.     sample_lb = sample_lb, sample_ub = sample_ub)

```

```

107.   tryCatch(
108.     {
109.       res <- rma.mv(esd, esdv, mods = ~factor(num), random = ~1|id/num, data = dat)
110.       rob <- robust(res, cluster = dat$id) #use cluster robust inference methods
111.       mpval[i] <- rob$QMp
112.       difb[i] <- rob$b[2]},
113.     error=function(error_message) {
114.       message(error_message)
115.       return(NA)
116.     }
117.   )
118. }
119.
120. mean(mpval <= .05, na.rm = TRUE) # mean rejection rate with alpha = .05
121. mean(difb, na.rm = TRUE) # mean estimate of difference in intervention effect between time
    points
122.
123.

```

To conduct a simulation, adjust the following settings:

lters: Number of meta-analyses to simulate (warning, the simulation can take a long time to run if this number is large)

nSims: Number of studies per meta-analysis.

cxa: The size of the effect to add to the first time point for the control group. Effects are scaled to Cohen's *d*.

exa: The size of the effect to add to the first time point for the experimental group.

cxb: The size of the effect to add to the second time point for the control group.

exb: The size of the effect to add to the second time point for the experimental group.

rho: The correlation between time points in the population, prior to adding intervention effects.

sample_lb: The lower bound for number of participants per group in an experiment included in a simulated meta-analysis. Groups will be equal in size for each experiment.

sample_ub: The upper bound for number of participants per group.

This simulation can be extended to return additional results from meta-analysis models by adding containers above the simulation and specifying the output to save within the simulation.