Supplement for 'Domain-general cognitive motivation: evidence from economic decision-making'

Jennifer L. Crawford

10/1/2021

Supplemental Information & Analyses

```
rm(list=ls())

#Packages
library(brms); library(bayestestR); library(BayesFactor); library(correlation); library(knitr);
library(RColorBrewer); library(tidyverse);
source("summarySEwithin2.R")

#Package versions used to run the analyses reported in the manuscript
##R version 4.1.0
##BayesFactor_0.9.12-4.2, bayestestR_0.10.5, brms_2.16.1, correlation_0.6.1, knitr_1.33,
##RColorBrewer_1.1-2, tidyverse_1.3.1

#Create data directories
#Cog-ED
coged.wm.path<-"https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Discounting/MDD_WMC
coged.wm.full.path <-"https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Discounting/MD
coged.speech.path<-"https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Discounting/MDD_
#Individual Difference Questionnaires
NCS.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Individual-Difference-Q
SPSRQ.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Individual-Difference
BISBAS.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Individual-Differenc
GRAPES.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Individual-Differenc
#Working Memory Capacity
LSpan.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Working-Memory-Capaci
OSpan.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Working-Memory-Capaci
SymmSpan.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Working-Memory-Cap
#complete subject list
subjects.path <- "https://raw.githubusercontent.com/jlcrawford/MDD/master/Data/Online/Discounting/subjec
#Make data frames for Cog-ED and demographics info
coged.wm<- read.csv(coged.wm.path, header = T)
coged.wm.full <- read.csv(coged.wm.full.path, header = T)
coged.speech<- read.csv(coged.speech.path, header = T)
#Make data frames for individual difference questionnaires
NCS <- read.csv(NCS.path, header = T)
SPSRQ <- read.csv(SPSRQ.path, header = T)
BISBAS <- read.csv(BISBAS.path, header = T)
```

```
GRAPES <- read.csv(GRAPES.path, header = T)
#Make data frames for working memory capacity tasks
LSpan <- read.csv(LSpan.path, header = T)
OSpan <- read.csv(OSpan.path, header = T)
SymmSpan <- read.csv(SymmSpan.path, header = T)
#Make data frame for usable subject info (i.e., subjects who have completed all tasks and questionnaires
Subjects <- read.csv(subjects.path, header = F)
colnames(Subjects) <- "subjectid"
```

Removing Participants who have an average SV >1

As an additional follow-up, when we removed all participants who had an average subjective value estimate >1 (i.e., participants who almost always chose the high-effort option), the same pattern of results holds; there is a positive relationship between effort discounting across working memory and speech comprehension domains, r = 0.31 [0.16, 0.45], BF10= 21.91, which remains after controlling for task difficulty and performance, r = 0.37 [0.23, 0.51], BF10= 230.33, and individual differences in working memory capacity and reward sensitivity, r = 0.39 [0.26, 0.53], BF10= 563.18.

Zero-order correlation between working memory and speech subjective value estimates

```
#Cog-ED Data
#clean data frame(s) with Cog-ED subjective value (SV) estimates and transform data so that SV
#estimates are equivalent across both domains (i.e., speech, WM)

##working memory
d.coged.wm <- coged.wm %>% select(subjectid,completed,fixedAmount_N2_1,
                            fixedAmount_N2_2,fixedAmount_N2_3,
                            fixedAmount_N3_1,fixedAmount_N3_2,
                            fixedAmount_N3_3,fixedAmount_N4_1,
                            fixedAmount_N4_2,fixedAmount_N4_3,
                            IP12_1,IP12_2,IP12_3,IP13_1,IP13_2,IP13_3,
                            IP14_1,IP14_2,IP14_3) %>%
  filter(completed == 1) %>%
  group_by(subjectid) %>%
  mutate(Domain = "WM",
         domainCode = 0,
         SV2_1 = ifelse(fixedAmount_N2_1 == "X", IP12_1/2, ((2-IP12_1)/2)+1),
         SV2_2 = ifelse(fixedAmount_N2_2 == "X", IP12_2/3, ((3-IP12_2)/3)+1),
         SV2_3 = ifelse(fixedAmount_N2_3 == "X", IP12_1/4, ((4-IP12_3)/4)+1),
         SV3_1 = ifelse(fixedAmount_N3_1 == "X", IP13_1/2, ((2-IP13_1)/2)+1),
         SV3_2 = ifelse(fixedAmount_N3_2 == "X", IP13_2/3, ((3-IP13_2)/3)+1),
         SV3_3 = ifelse(fixedAmount_N3_3 == "X", IP13_1/4, ((4-IP13_3)/4)+1),
         SV4_1 = ifelse(fixedAmount_N4_1 == "X", IP14_1/2, ((2-IP14_1)/2)+1),
         SV4_2 = ifelse(fixedAmount_N4_2 == "X", IP14_2/3, ((3-IP14_2)/3)+1),
         SV4_3 = ifelse(fixedAmount_N4_3 == "X", IP14_3/4, ((4-IP14_3)/4)+1),
         SV_red = (SV2_1 + SV2_2 + SV2_3)/3,
         SV_blue = (SV3_1 + SV3_2 + SV3_3)/3,
         SV_purple = (SV4_1 + SV4_2 + SV4_3)/3)

##speech comprehension
```

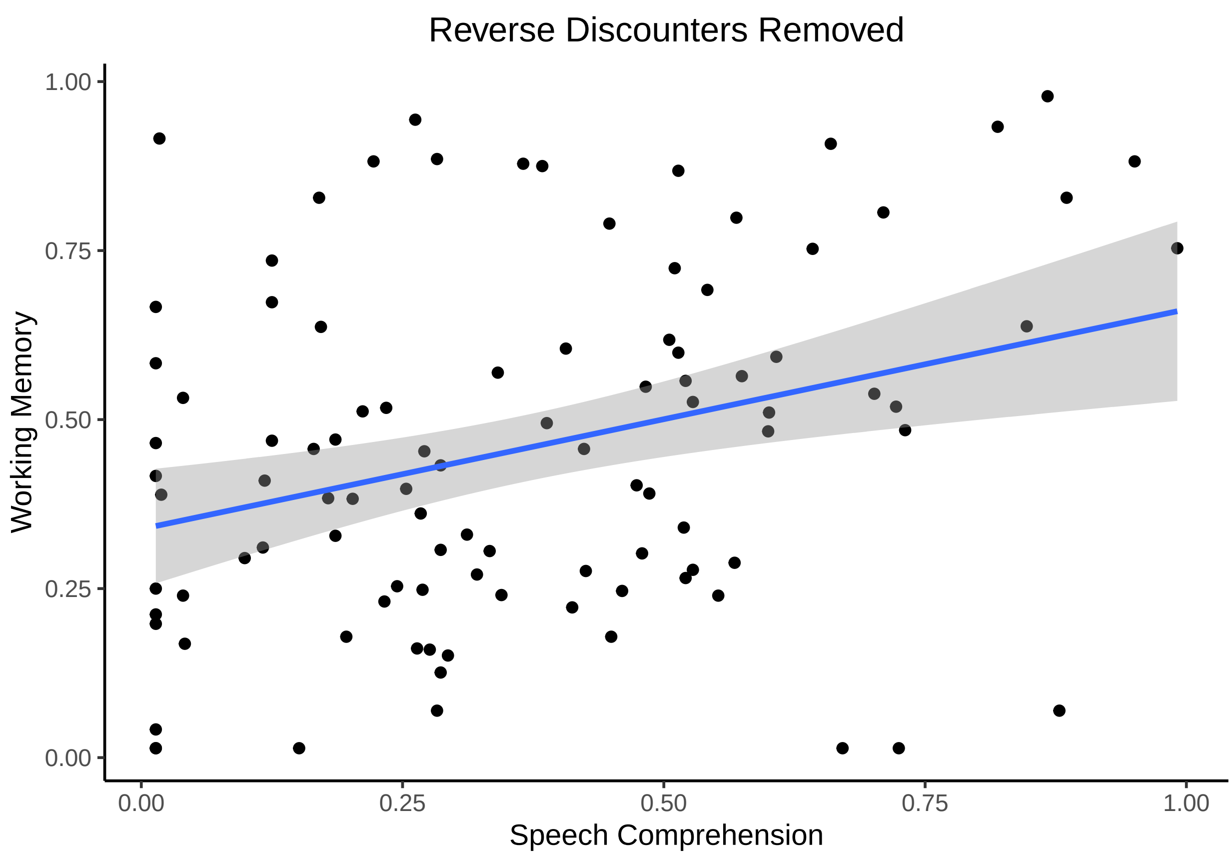
```r
d.coged.speech <- coged.speech %>%
  select(subjectid,completed,fixedAmount_N2_1,fixedAmount_N2_2,fixedAmount_N2_3,
                            fixedAmount_N3_1,fixedAmount_N3_2,fixedAmount_N3_3,
                            fixedAmount_N4_1,fixedAmount_N4_2,fixedAmount_N4_3,
                            IP12_1,IP12_2,IP12_3,IP13_1,IP13_2,IP13_3,IP14_1,IP14_2,IP14_3) %>%
  filter(completed == 1) %>%
  group_by(subjectid) %>%
  mutate(Domain = "Speech",
         domainCode = 1,
         SV2_1 = ifelse(fixedAmount_N2_1 == "X", IP12_1/2, ((2-IP12_1)/2)+1),
         SV2_2 = ifelse(fixedAmount_N2_2 == "X", IP12_2/3, ((3-IP12_2)/3)+1),
         SV2_3 = ifelse(fixedAmount_N2_3 == "X", IP12_1/4, ((4-IP12_3)/4)+1),
         SV3_1 = ifelse(fixedAmount_N3_1 == "X", IP13_1/2, ((2-IP13_1)/2)+1),
         SV3_2 = ifelse(fixedAmount_N3_2 == "X", IP13_2/3, ((3-IP13_2)/3)+1),
         SV3_3 = ifelse(fixedAmount_N3_3 == "X", IP13_1/4, ((4-IP13_3)/4)+1),
         SV4_1 = ifelse(fixedAmount_N4_1 == "X", IP14_1/2, ((2-IP14_1)/2)+1),
         SV4_2 = ifelse(fixedAmount_N4_2 == "X", IP14_2/3, ((3-IP14_2)/3)+1),
         SV4_3 = ifelse(fixedAmount_N4_3 == "X", IP14_3/4, ((4-IP14_3)/4)+1),
         SV_red = (SV2_1 + SV2_2 + SV2_3)/3,
         SV_blue = (SV3_1 + SV3_2 + SV3_3)/3,
         SV_purple = (SV4_1 + SV4_2 + SV4_3)/3)
#Merge WM and Speech Cog-ED data frames
coged.merged <- rbind(d.coged.wm, d.coged.speech)

#Filter out subjects who have not completed all tasks in the protocol
coged.merged <-inner_join(Subjects, coged.merged)

#Add dummy variables (task, domain) for multilevel models
d.coged.SV <- coged.merged %>% select(subjectid,Domain,domainCode, SV_red, SV_blue, SV_purple) %>%
  pivot_longer(names_to = "tmp", values_to = "SV", -c(subjectid,Domain,domainCode)) %>%
  separate(col = tmp, into=c(NA,"Task"), sep = "_") %>%
  mutate(taskCode = factor(Task, levels=c("red","blue","purple"), labels=c(-1,0,1)))
d.coged.SV$taskCode <- as.numeric(d.coged.SV$taskCode)
d.coged.SV$domainCode <- as.numeric(d.coged.SV$domainCode)

#Correlating Average SV (within-subj) across domains
average.SV.outliers <- coged.merged %>% select(subjectid, Domain, SV_red, SV_blue, SV_purple) %>%
  group_by(subjectid, Domain) %>%
  dplyr::summarise(SV_avg = (SV_red + SV_blue + SV_purple)/3) %>%
  pivot_wider(values_from = "SV_avg", names_from = "Domain") %>%
  filter(Speech < 1) %>% filter(WM < 1)

#Testing for correlation between cognitive effort discounting across working memory & speech domains
CogED.cor.adj <- cor_test(data = average.SV.outliers, x = "Speech", y = "WM",
                          bayesian = TRUE, bayesian_prior = 0.707107)
#Summarize Bayes Factor from correlation
CogED.cor.adj
```

99 participants inlcuded in analyses

```
## Parameter1 | Parameter2 |  rho |       95% CI |       pd | % in ROPE |               Prior |      BF
## ---------------------------------------------------------------------------------------------------
## Speech     |         WM | 0.31 | [0.15, 0.44] | 99.88%** |     1.45% | Beta (1.41 +- 1.41) | 21.91**
```

```
##
## Observations: 99
```

```
#Plot of correlation between working memory & speech comprehension domains
fig.outlier.rm <- ggplot(average.SV.outliers, aes(Speech, WM)) +
   theme(plot.title = element_text(hjust = 0.5), panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(), panel.background = element_blank(),
         axis.line = element_line(colour = "black")) +
  geom_point() + geom_smooth(method=lm) +ggtitle("Reverse Discounters Removed") +
    xlab("Speech Comprehension") + ylab("Working Memory")
fig.outlier.rm
```



Controlling for task level and performance

Familiarization Phase Performance

Speech

```
performance.speech <- coged.speech %>% select(subjectid, completed, percentCorrect_N1,
                                             percentCorrect_N2, percentCorrect_N3, percentCorrect_N4) %
   group_by(subjectid) %>% filter(completed == 1) %>% select(-completed) %>%
  pivot_longer(names_to = "level", values_to = "performance", -c(subjectid)) %>%
  separate(col = level, into=c(NA,"Task"), sep = "_") %>% inner_join(Subjects)
```

```r
performance.speech$task <- factor(performance.speech$Task, levels = c("N1","N2","N3","N4"),
                                  labels = c("black","red","blue","purple"))

performance_sum <- summarySEwithin2(performance.speech, measurevar = "performance",
                                    withinvars = c("Task"), idvar = "subjectid")
performance_sum$Task <- factor(performance_sum$Task, levels = c("N1","N2","N3","N4"),
                               labels = c("0 SNR","-4 SNR","-8 SNR","-12 SNR"))
```

Working Memory

```r
performance.wm <- coged.wm %>% select(subjectid, completed, hitrate_N1, CRrate_N1,
                                      hitrate_N2, CRrate_N2, hitrate_N3, CRrate_N3,
                                      hitrate_N4, CRrate_N4) %>%
   group_by(subjectid) %>% filter(completed == 1) %>% select(-completed) %>%
  pivot_longer(names_to = "level", values_to = "performance", -c(subjectid)) %>%
  separate(col = level, into=c("Metric","Task"), sep = "_") %>%
  pivot_wider(names_from = Metric, values_from = performance)  %>% inner_join(Subjects)
performance.wm$task <- factor(performance.wm$Task, levels = c("N1","N2","N3","N4"),
                              labels = c("black","red","blue","purple"))

performance.sum.wm <- summarySEwithin2(performance.wm, measurevar = "hitrate",
                                       withinvars = c("Task"), idvar = "subjectid")
performance.sum.wm$Task <- factor(performance.sum.wm$Task, levels = c("N1","N2","N3","N4"),
                                  labels = c("1-back","2-back","3-back","4-back"))

performance.wm.RT <- coged.wm.full %>% select(subjectid, blockcode, phase, response, latency) %>%
  filter(phase == 1) %>%
  rename(task = "blockcode") %>% filter(task != "ratingSummary") %>% filter(response != 0)
performance.wm.RT$task <- factor(performance.wm.RT$task, levels = c("1back","2back","3back","4back"),
                                 labels = c("black","red","blue","purple"))

performance.wm.RT.sum <-inner_join(performance.wm.RT, Subjects) %>% group_by(subjectid, task) %>%
  summarise(meanRT = mean(latency))
```

```r
#Working Memory Cog-ED
#Summarize average performance on N-Back
d.coged.wm.clean <- d.coged.wm %>% select(subjectid, SV_red, SV_blue, SV_purple) %>%
  pivot_longer(names_to = "tmp", values_to = "SV", -subjectid) %>%
   separate(col = tmp, into=c(NA,"task"), sep = "_")

d.coged.wm.partial <- d.coged.wm.clean %>% group_by(subjectid,task) %>%
  summarise(meanSV = mean(SV)) %>%
  inner_join(performance.wm, by = c("subjectid","task")) %>%
  inner_join(performance.wm.RT.sum) %>%
  mutate(taskCode = factor(task, levels =c( "black","red","blue","purple"),
                           labels = c(-2,-1,0,1)),
         FArate = 1-CRrate,
         HR_z = scale(hitrate),
         FAR_z = scale(FArate),
         dPrime = HR_z - FAR_z)
```

```r
d.coged.wm.partial$taskCode <- as.numeric(d.coged.wm.partial$taskCode)

#Speech Cog-ED
d.coged.speech.clean <- d.coged.speech %>% select(subjectid, SV_red, SV_blue, SV_purple) %>%
  pivot_longer(names_to = "tmp", values_to = "SV", -subjectid) %>%
   separate(col = tmp, into=c(NA,"task"), sep = "_")

d.coged.speech.partial <- d.coged.speech.clean %>% group_by(subjectid,task) %>%
  summarise(meanSV = mean(SV)) %>%
  inner_join(performance.speech, by = c("subjectid","task")) %>%
  mutate(taskCode = factor(task, levels =c("red","blue","purple"),
                          labels = c(-1,0,1)))
d.coged.speech.partial$taskCode <- as.numeric(d.coged.speech.partial$taskCode)
```

```r
#Working Memory Cog-ED
#Summarize average performance on N-Back
outlier.subjs <- average.SV.outliers$subjectid %>% as_tibble()
colnames(outlier.subjs) <- "subjectid"

d.coged.wm.partial.outlier <- inner_join(d.coged.wm.partial, outlier.subjs)

m.SV.wm.partial.outlier <- brm(data = d.coged.wm.partial.outlier, meanSV ~ taskCode +
                                 hitrate + CRrate + meanRT + (1 | subjectid),
                               file = "models/m.SV.wm.partial.outlier.rds")
summary(m.SV.wm.partial.outlier)
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: meanSV ~ taskCode + hitrate + CRrate + meanRT + (1 | subjectid)
##    Data: d.coged.wm.partial.outlier (Number of observations: 297)
##   Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup draws = 4000
##
## Group-Level Effects:
## ~subjectid (Number of levels: 99)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.23      0.02     0.20     0.28 1.00     1279     2301
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept     0.58      0.13     0.32     0.84 1.00     2274     2871
## taskCode     -0.08      0.01    -0.11    -0.05 1.00     4691     3035
## hitrate       0.20      0.06     0.08     0.30 1.00     2906     3218
## CRrate        0.06      0.09    -0.12     0.25 1.00     2158     2749
## meanRT       -0.00      0.00    -0.00     0.00 1.00     2674     3069
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.18      0.01     0.16     0.20 1.00     2962     2712
##
## Draws were sampled using sampling(NUTS). 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).
```

```r
subj.resid.wm.outlier <- m.SV.wm.partial.outlier[["data"]][["subjectid"]] %>% as_tibble()
colnames(subj.resid.wm.outlier) <- "subjectid"
res.WM.outlier <- resid(m.SV.wm.partial.outlier) %>% as_tibble() %>% select(Estimate)
colnames(res.WM.outlier) <- "resid.wm"
res.subj.WM.outlier <- cbind(subj.resid.wm.outlier, res.WM.outlier)

#Speech Cog-ED
d.coged.speech.partial.outlier <- inner_join(d.coged.speech.partial, outlier.subjs)

m.SV.speech.partial.outlier <- brm(data = d.coged.speech.partial.outlier, meanSV ~ taskCode +
                                     performance + (1 | subjectid),
                                   file = "models/m.SV.speech.partial.outlier.rds")
summary(m.SV.speech.partial.outlier)
```

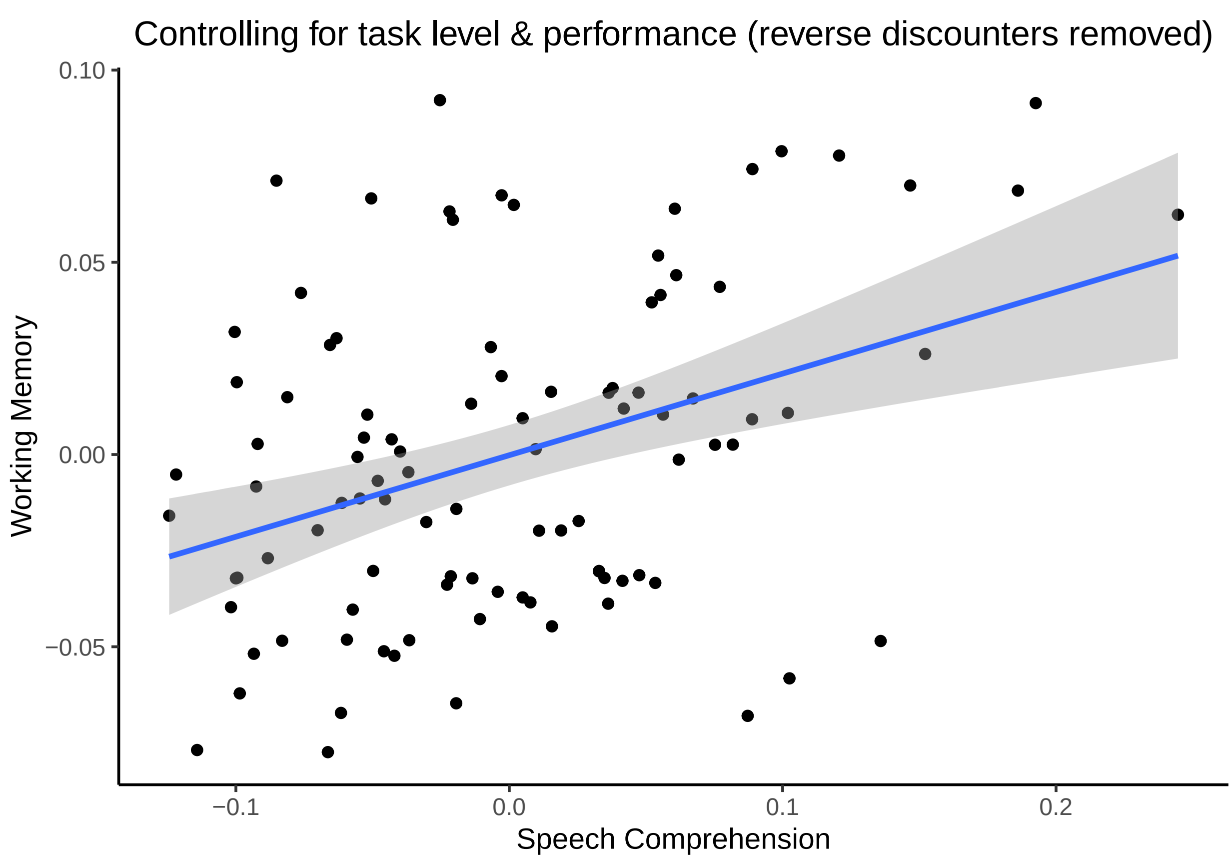
```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: meanSV ~ taskCode + performance + (1 | subjectid)
##    Data: d.coged.speech.partial.outlier (Number of observations: 297)
##   Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup draws = 4000
##
## Group-Level Effects:
## ~subjectid (Number of levels: 99)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.20      0.02     0.16     0.25 1.00     1881     2884
##
## Population-Level Effects:
##             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept       0.35      0.13     0.08     0.61 1.00     2976     2978
## taskCode       -0.08      0.04    -0.15     0.00 1.00     3069     2826
## performance     0.00      0.00     0.00     0.01 1.00     2881     3361
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.24      0.01     0.21     0.26 1.00     3169     3319
##
## Draws were sampled using sampling(NUTS). 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).
```

```r
subj.resid.speech.outlier <- m.SV.speech.partial.outlier[["data"]][["subjectid"]] %>% as_tibble()
colnames(subj.resid.speech.outlier) <- "subjectid"
res.speech.outlier <-residuals(m.SV.speech.partial.outlier) %>% as_tibble() %>% select(Estimate)
colnames(res.speech.outlier) <- "resid.speech"
res.subj.Speech.outlier <- cbind(subj.resid.speech.outlier, res.speech.outlier)

SV.resids.outlier <- cbind(res.subj.WM.outlier, res.speech.outlier) %>% group_by(subjectid) %>%
  summarise(mean.resid.wm = mean(resid.wm), mean.resid.speech = mean(resid.speech))
#Testing for correlation between cognitive effort discounting across working memory & speech domains
#controlling for task performance
CogED.cor.partial.outlier <- cor_test(data = SV.resids.outlier, x = "mean.resid.wm",
                                      y = "mean.resid.speech", bayesian = TRUE,
                                      bayesian_prior = 0.707107)
```

```
#Summarize Bayes Factor from correlation controlling for task performance
CogED.cor.partial.outlier
```

```
## Parameter1    |        Parameter2 |  rho |       95% CI |      pd | % in ROPE |               Prior
## ---------------------------------------------------------------------------------------------------
## mean.resid.wm | mean.resid.speech | 0.37 | [0.22, 0.50] | 100%*** |     0.33% | Beta (1.41 +- 1.41)
##
## Observations: 99
```

```
#Plot of correlation between working memory & speech comprehension domains controlling for task level &
fig.resid.outlier <- ggplot(SV.resids.outlier, aes(mean.resid.speech, mean.resid.wm)) +
   theme(plot.title = element_text(hjust = 0.5), panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(), panel.background = element_blank(),
         axis.line = element_line(colour = "black")) +
  geom_point() + geom_smooth(method=lm) +
  ggtitle("Controlling for task level & performance (reverse discounters removed)") +
    xlab("Speech Comprehension") + ylab("Working Memory")
fig.resid.outlier
```



Partial correlation controlling for WMC and reward sensitivity (from residualized SV estimates)

Reward Motivation (BIS/BAS, SPSRQ, GRAPES)

```
#BIS/BAS
#Importing and cleaning BIS/BAS
BISBAS.clean <- BISBAS %>% select(c(subjectid,completed, BAS_Drive, BAS_Fun, BAS_Reward, BIS)) %>% disti
BISBAS.SV <- inner_join(average.SV.outliers, BISBAS.clean)

#SPSRQ
#Importing and cleaning SPSRQ
SPSRQ.clean <- SPSRQ %>% select(c(subjectid, completed, SensitivityToReward, SensitivityToPunishment)) %
SPSRQ.SV <- inner_join(average.SV.outliers, SPSRQ.clean)

#GRAPES
GRAPES.clean <- GRAPES %>% select(c(subjectid, ends_with("response"))) %>% distinct(subjectid, .keep_all
  mutate(GRAPES.rew = q1_response + q4_response + q6_response + q7_response + q9_response + q10_respons
         q16_response + q16_response + q19_response + q20_response + q21_response + q25_response + q26_r
         GRAPES.pun = q2_response + q3_response + q5_response + q8_response + q11_response + q12_respons
         q14_response + q18_response + q22_response + q23_response + q24_response + q28_response + q29_r
GRAPES.SV <- inner_join(average.SV.outliers, GRAPES.clean)
```

Working Memory Capacity (Listing Span, Operation Span, Symmetry Span)

```
#Importing and cleaning WMC measures
#Listening Span
LSpan.clean <- LSpan %>% select(c(subjectid, completed, ListeningSpanScore)) %>%
  distinct(subjectid, .keep_all=T)
LSpan.SV <- inner_join(average.SV.outliers, LSpan.clean)

#Operation Span
OSpan.clean <- OSpan %>% select(c(subjectid, completed, ospan)) %>%
  distinct(subjectid, .keep_all=T)
OSpan.SV <- inner_join(average.SV.outliers, OSpan.clean)

#Symmetry Span
SymSpan.clean <- SymmSpan %>% select(c(subjectid, completed, sspan)) %>%
  distinct(subjectid, .keep_all=T)
SymSpan.SV <- inner_join(average.SV.outliers, SymSpan.clean)
```

```
#Create data frame with WMC measures, get z-scores, and create a composite measure
LSpan.comp <- LSpan.SV %>% select(-c(Speech, WM))
LSpan.comp$LSpan.z <- scale(LSpan.comp$ListeningSpanScore)
OSpan.comp <- OSpan.SV %>% select(-c(Speech, WM))
OSpan.comp$OSpan.z <- scale(OSpan.comp$ospan)
SymSpan.comp <- SymSpan.SV %>% select(-c(Speech, WM))
SymSpan.comp$SSpan.z <- scale(SymSpan.comp$sspan)

WMC.outlier <- inner_join(LSpan.comp, OSpan.comp, by = "subjectid") %>%
```

```
  inner_join(SymSpan.comp, by = "subjectid") %>%
  filter(completed.x == 1) %>% filter(completed.y == 1) %>% filter(completed == 1) %>%
  select(-c("completed.x","completed.y","completed")) %>%
  mutate(WMC.composite = (LSpan.z + OSpan.z + SSpan.z)) %>%
  select(subjectid, WMC.composite)

#Create data frame with reward sensitivity measures, get z-scores, and create a composite measure
BISBAS.comp <- BISBAS.SV %>% select(-c(Speech, WM, BAS_Drive, BAS_Fun, BAS_Reward, BIS))
BISBAS.comp$BAS.z <- scale(BISBAS.comp$BAS_total)
SPSRQ.comp <- SPSRQ.SV %>% select(-c(Speech, WM, SensitivityToPunishment))
SPSRQ.comp$SPSRQ.rew.z <- scale(SPSRQ.comp$SensitivityToReward)
GRAPES.comp <- GRAPES.SV %>% select(c(subjectid, GRAPES.rew))
GRAPES.comp$GRAPES.rew.z <- scale(GRAPES.comp$GRAPES.rew)

Reward.composite.outlier <- inner_join(BISBAS.comp, SPSRQ.comp, by = "subjectid") %>%
  inner_join(GRAPES.comp, by = "subjectid") %>%
  filter(completed.x == 1) %>% filter(completed.y == 1) %>%
  select(-c("completed.x","completed.y")) %>%
  mutate(Rew.composite = (BAS.z + SPSRQ.rew.z + GRAPES.rew.z)) %>%
  select(subjectid, Rew.composite)
```

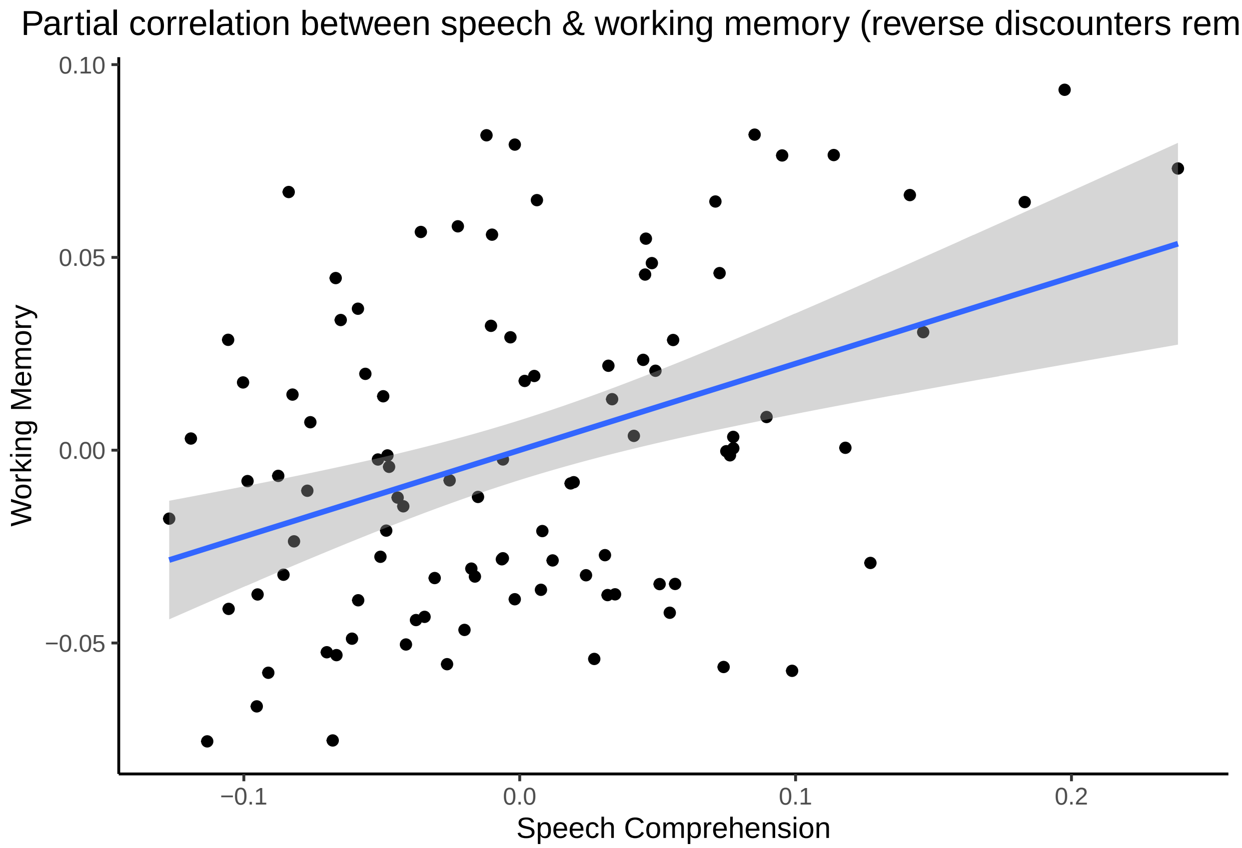
Partial correlation controlling for WMC and reward sensitivity (from residualized SV estimates)

```
#Testing for partial correlation between residuals (from stage two) controlling for WMC and reward sens
SV.composite.resid.outlier <- inner_join(WMC.outlier, Reward.composite.outlier, by = "subjectid") %>%
  inner_join(SV.resids.outlier, by = "subjectid")
SV.composite.resid.outlier.clean <- cbind(SV.composite.resid.outlier$WMC.composite,
                                          SV.composite.resid.outlier$Rew.composite,
                                          SV.composite.resid.outlier$mean.resid.speech,
                                          SV.composite.resid.outlier$mean.resid.wm) %>% as_tibble()
colnames(SV.composite.resid.outlier.clean) <- c("WMC", "Reward", "Speech", "WM")

WMC.resid.cor.outlier <- cor_test(data = SV.composite.resid.outlier.clean, x = "WM", y = "Speech",
                                  bayesian = TRUE, partial_bayesian = TRUE, bayesian_prior  = 0.707107)
#Summarize Bayes Factor from correlation
WMC.resid.cor.outlier
```

```
## Parameter1 | Parameter2 |  rho |       95% CI |      pd | % in ROPE |              Prior |        BF
## ------------------------------------------------------------------------------------------------------
## WM         |     Speech | 0.39 | [0.24, 0.51] | 100%*** |     0.18% | Beta (1.41 +- 1.41) | 563.21***
##
## Observations: 99
```

```
#WM Cog-ED
d.coged.wm.partial.outlier.plot <- inner_join(d.coged.wm.partial.outlier, WMC.outlier,
                                              by = "subjectid") %>%
  inner_join(Reward.composite.outlier, by = "subjectid")
m.SV.wm.partial.outlier.plot <- brm(data = d.coged.wm.partial.outlier.plot, meanSV ~ taskCode +
                                    hitrate + CRrate + meanRT + WMC.composite + Rew.composite + (1 | sul
                                    file = "models/m.SV.wm.partial.outlier.plot.rds")
```

```r
subj.resid.wm.outlier.plot <- m.SV.wm.partial.outlier.plot[["data"]][["subjectid"]] %>% as_tibble()
colnames(subj.resid.wm.outlier.plot) <- "subjectid"
res.WM.outlier.plot <- residuals(m.SV.wm.partial.outlier.plot) %>% as_tibble() %>% select(Estimate)
colnames(res.WM.outlier.plot) <- "resid.wm"
res.subj.WM.outlier.plot <- cbind(subj.resid.wm.outlier.plot, res.WM.outlier.plot)

#Speech Cog-ED
d.coged.speech.partial.outlier.plot <- inner_join(d.coged.speech.partial.outlier, WMC.outlier,
                                                  by = "subjectid") %>%
  inner_join(Reward.composite.outlier, by = "subjectid")
m.SV.speech.partial.outlier.plot <- brm(data = d.coged.speech.partial.outlier.plot, meanSV ~ taskCode +
                                          performance + WMC.composite + Rew.composite + (1 | subjectid)
                                        file = "models/m.SV.speech.partial.outlier.plot.rds")

subj.resid.speech.outlier.plot <- m.SV.speech.partial.outlier.plot[["data"]][["subjectid"]] %>% as_tibbl
colnames(subj.resid.speech.outlier.plot) <- "subjectid"
res.speech.outlier.plot <-residuals(m.SV.speech.partial.outlier.plot) %>% as_tibble() %>%
  select(Estimate)
colnames(res.speech.outlier.plot) <- "resid.speech"
res.subj.Speech.outlier.plot <- cbind(subj.resid.speech.outlier.plot, res.speech.outlier.plot)

SV.resids.outlier.plot <- cbind(res.subj.WM.outlier.plot, res.speech.outlier.plot) %>%
  group_by(subjectid) %>%
  summarise(mean.resid.wm = mean(resid.wm), mean.resid.speech = mean(resid.speech))
#Testing for correlation between cognitive effort discounting across working memory & speech domains
#controlling for task performance
CogED.cor.partial.outlier.plot <- cor_test(data = SV.resids.outlier.plot,
                                           x = "mean.resid.wm", y = "mean.resid.speech",
                                           bayesian = TRUE, bayesian_prior = 0.707107)

#Plot of correlation between working memory & speech comprehension domains
#controlling for task level, performance, WMC, and reward sensitivity
fig.resid.outlier.plot <- ggplot(SV.resids.outlier.plot, aes(mean.resid.speech, mean.resid.wm)) +
   theme(plot.title = element_text(hjust = 0.5), panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(), panel.background = element_blank(),
         axis.line = element_line(colour = "black")) +
  geom_point() + geom_smooth(method=lm) +
  ggtitle("Partial correlation between speech & working memory (reverse discounters removed)") +
    xlab("Speech Comprehension") + ylab("Working Memory")
fig.resid.outlier.plot
```



NASA TLX

Participants completed NASA ratings after each load level during the familiarization phase (likert scale: 1-21; higher values indicate greater endorsement) As reported in the main text, there was a main effect of task load across ratings of mental demand B= 3.64 [2.94, 4.31], SD=0.35, effort B= 2.52 [1.93, 3.14], SD=0.31, and frustration B= 0.98 [0.20, 1.73], SD=0.39. In addition, there was also a main effect of domain for self-reported ratings of mental demand, B= 3.10 [1.88, 4.30], SD=0.61, and effort, B= 2.65 [1.62, 3.73], SD=0.54., such that ratings of subjective mental demand and effort were greater for the speech comprehension task, relative to the working memory task. Frustration ratings did not differ across task domain, B= 0.35 [-0.95, 1.67], SD=0.68. Finally, there was an interaction between task load and domain across ratings of mental demand, B= -0.57 [-0.99, -0.13], SD=0.22, and frustration, B= 0.72 [0.24, 1.20], SD=0.25. There was no interaction between task load and domain for ratings of effort, B= -0.34 [-0.74, 0.04], SD=0.20.

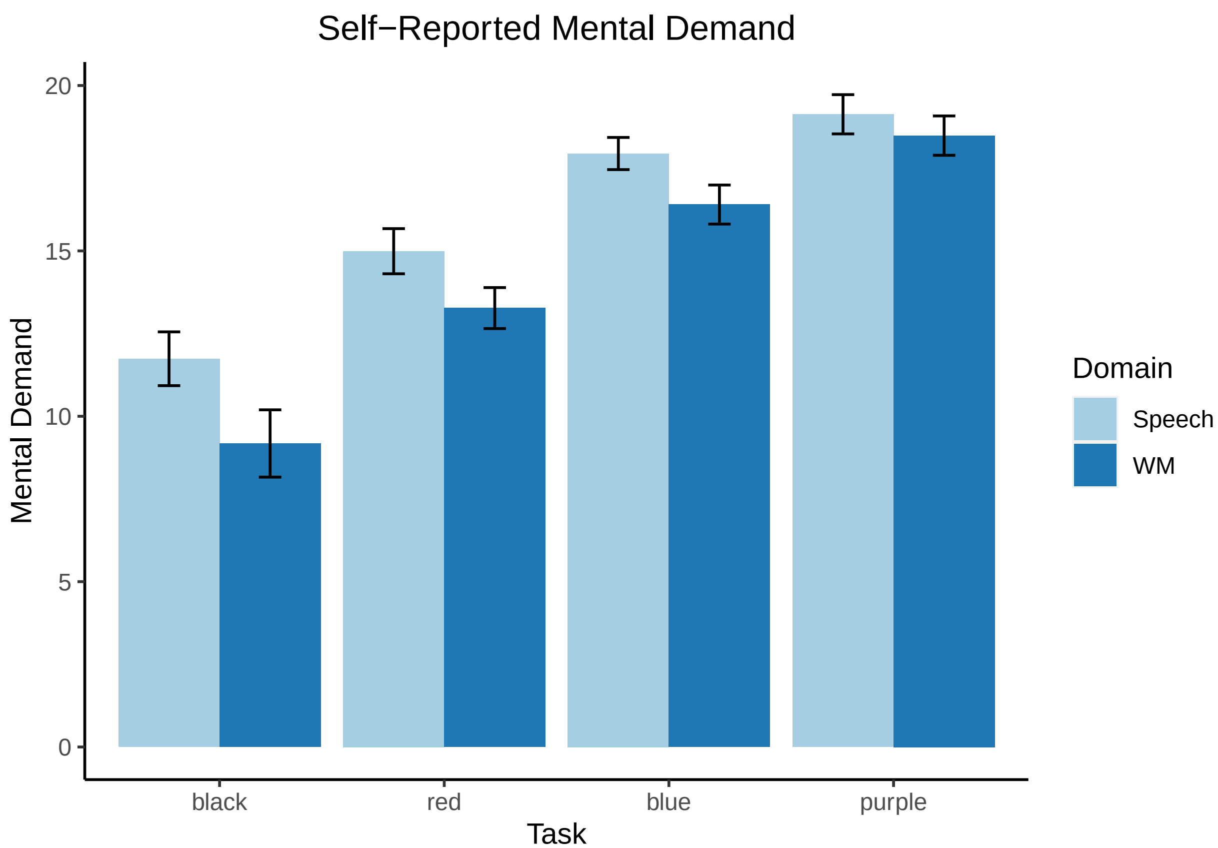
```
#Mental Demand Ratings
NASA.m.demand.wm <- coged.wm %>% select(subjectid, completed, mentaldemand_1,
                                        mentaldemand_2, mentaldemand_3, mentaldemand_4) %>%
  group_by(subjectid) %>%
  filter(completed == 1) %>%
  mutate(Domain = "WM")

NASA.m.demand.speech <- coged.speech %>% select(subjectid, completed, mentaldemand_1,
                                                mentaldemand_2, mentaldemand_3, mentaldemand_4) %>%
  group_by(subjectid) %>%
  filter(completed == 1) %>%
```

```r
  mutate(Domain = "Speech")

NASA.m.demand <- rbind(NASA.m.demand.wm,NASA.m.demand.speech) %>% select(-completed) %>%
  pivot_longer(names_to = "mental_demand", values_to = "rating", -c(subjectid,Domain)) %>%
  separate(col = mental_demand, into=c(NA,"Task"), sep = "_") %>%
  mutate(taskCode = factor(Task, levels=c(1,2,3,4), labels=c(0,1,2,3)),
         domainCode = factor(Domain, levels = c("WM","Speech"), labels = c(0,1)))

NASA.m.demand$taskCode <- as.numeric(NASA.m.demand$taskCode)
NASA.m.demand$domainCode <- as.numeric(NASA.m.demand$domainCode)
NASA_mdemand_sum <- summarySEwithin2(NASA.m.demand, measurevar = "rating",
                                     withinvars = c("Task","Domain"), idvar = "subjectid")
NASA_mdemand_sum$Task <- factor(NASA_mdemand_sum$Task, levels = c(1,2,3,4),
                                labels = c("black","red","blue","purple"))

m.mentalDemand <- brm(data = NASA.m.demand, rating ~ taskCode*domainCode + (1 | subjectid),
                      file = "models/m.mentalDemand.rds")
summary(m.mentalDemand)
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: rating ~ taskCode * domainCode + (1 | subjectid)
##    Data: NASA.m.demand (Number of observations: 856)
##   Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup draws = 4000
##
## Group-Level Effects:
## ~subjectid (Number of levels: 107)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     2.65      0.23     2.23     3.12 1.00     1148     1789
##
## Population-Level Effects:
##                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept               3.50      0.97     1.58     5.41 1.00     2127     2549
## taskCode                3.69      0.35     3.04     4.39 1.00     2195     2274
## domainCode              3.09      0.60     1.91     4.27 1.00     2178     2553
## taskCode:domainCode    -0.59      0.22    -1.03    -0.17 1.00     2134     2405
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     3.65      0.09     3.47     3.84 1.00     4122     2960
##
## Draws were sampled using sampling(NUTS). 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).
```

```r
p.m.demand <- ggplot(NASA_mdemand_sum, aes(x=Task, y=rating, fill=Domain)) +
  theme(plot.title = element_text(hjust = 0.5), panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(), panel.background = element_blank(),
        axis.line = element_line(colour = "black")) +
  geom_bar(stat="identity", position=position_dodge()) +
  geom_errorbar(position=position_dodge(width=0.9), aes(ymin=rating-ci, ymax=rating+ci), width=.2) +
  xlab("Task") + ylab("Mental Demand") + ggtitle("Self-Reported Mental Demand")
```

```r
p.m.demand + labs(fill = "Domain") + scale_fill_brewer(palette = "Paired")
```

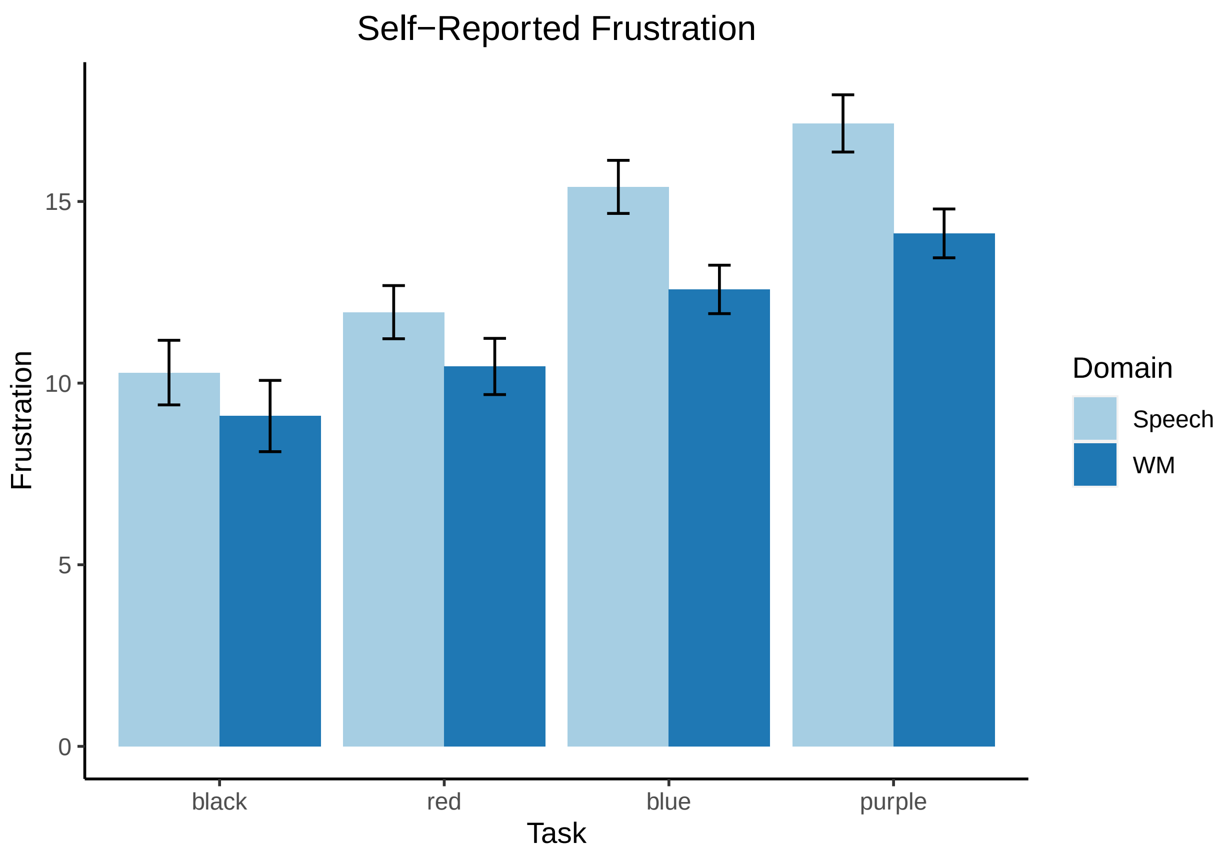



```r
#Frustration Ratings
NASA.frust.wm <- coged.wm %>% select(subjectid, completed, frustration_1,
                                     frustration_2, frustration_3, frustration_4) %>%
  group_by(subjectid) %>%
  filter(completed == 1) %>%
  mutate(Domain = "WM")

NASA.frust.speech <- coged.speech %>% select(subjectid, completed, frustration_1,
                                             frustration_2, frustration_3, frustration_4) %>%
  group_by(subjectid) %>%
  filter(completed == 1) %>%
  mutate(Domain = "Speech")

NASA.frust <- rbind(NASA.frust.wm,NASA.frust.speech) %>% select(-completed) %>%
  pivot_longer(names_to = "frustration", values_to = "rating", -c(subjectid, Domain)) %>%
  separate(col = frustration, into=c(NA,"Task"), sep = "_") %>%
  mutate(taskCode = factor(Task, levels=c(1,2,3,4), labels=c(0,1,2,3)),
         domainCode = factor(Domain, levels = c("WM","Speech"), labels = c(0,1)))
NASA.frust$taskCode <- as.numeric(NASA.frust$taskCode)
NASA.frust$domainCode <- as.numeric(NASA.frust$domainCode)

m.Frustration <- brm(data = NASA.frust, rating ~ taskCode*domainCode + (1 | subjectid),
                     file = "models/m.Frustration.rds")
```

```r
summary(m.Frustration)
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: rating ~ taskCode * domainCode + (1 | subjectid)
##    Data: NASA.frust (Number of observations: 856)
##   Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup draws = 4000
##
## Group-Level Effects:
## ~subjectid (Number of levels: 107)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     4.01      0.32     3.45     4.68 1.01      756     1000
##
## Population-Level Effects:
##                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept               6.81      1.19     4.55     9.16 1.00     1459     1982
## taskCode                1.04      0.41     0.24     1.83 1.00     1869     2464
## domainCode              0.43      0.70    -0.94     1.77 1.00     1977     2326
## taskCode:domainCode     0.68      0.26     0.18     1.18 1.00     1909     2505
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     4.11      0.11     3.91     4.32 1.00     3178     2981
##
## Draws were sampled using sampling(NUTS). 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).
```

```r
NASA_frust_sum <- summarySEwithin2(NASA.frust, measurevar = "rating",
                                   withinvars = c("Task","Domain"), idvar = "subjectid")
NASA_frust_sum$Task <- factor(NASA_frust_sum$Task, levels = c(1,2,3,4),
                              labels = c("black","red","blue","purple"))

p.frust <- ggplot(NASA_frust_sum, aes(x=Task, y=rating, fill=Domain)) +
  theme(plot.title = element_text(hjust = 0.5), panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(), panel.background = element_blank(),
        axis.line = element_line(colour = "black")) +
  geom_bar(stat="identity", position=position_dodge()) +
  geom_errorbar(position=position_dodge(width=0.9), aes(ymin=rating-ci, ymax=rating+ci), width=.2) +
  xlab("Task") + ylab("Frustration") + ggtitle("Self-Reported Frustration")
p.frust +  labs(fill = "Domain") + scale_fill_brewer(palette = "Paired")
```

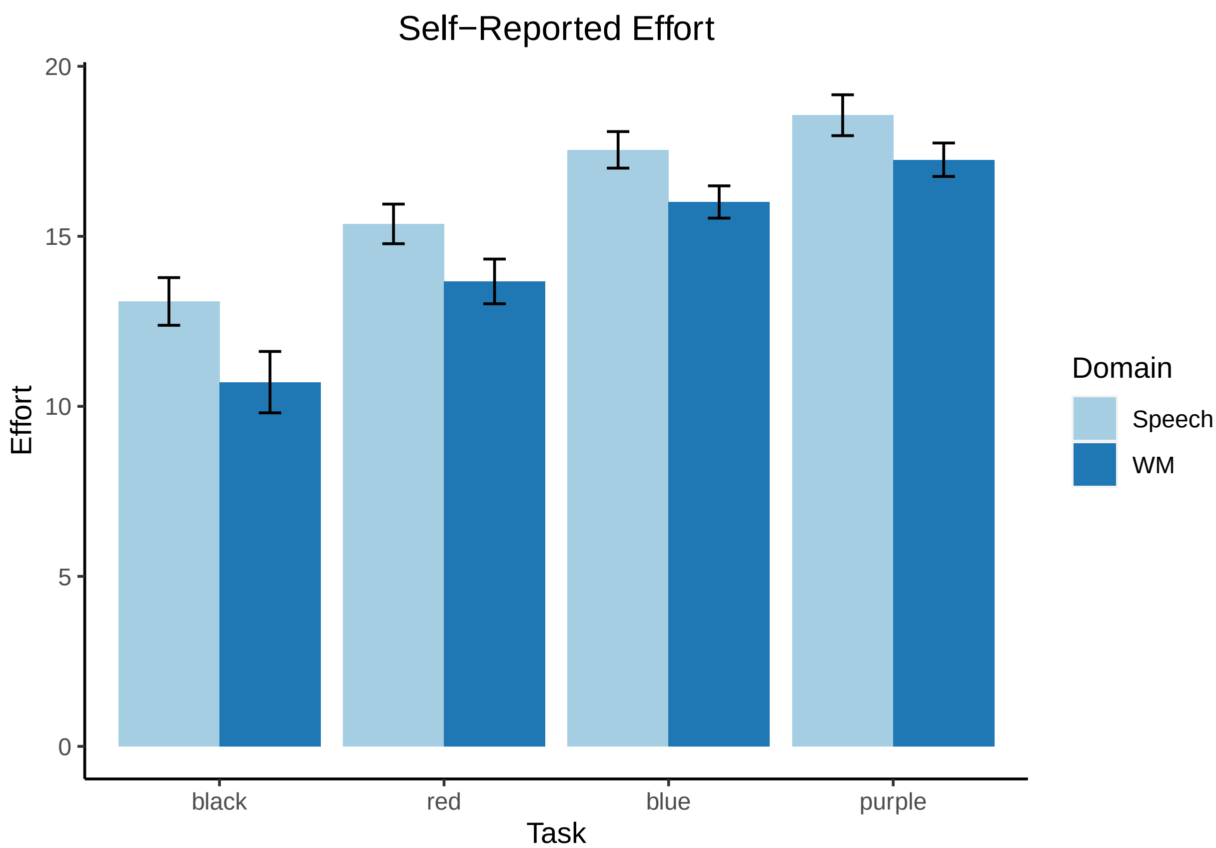



```
#Effort Ratings
NASA.effort.wm <- coged.wm %>% select(subjectid, completed, effort_1,
                                      effort_2, effort_3, effort_4) %>%
  group_by(subjectid) %>%
  filter(completed == 1) %>%
  mutate(Domain = "WM")

NASA.effort.speech <- coged.speech %>% select(subjectid, completed, effort_1,
                                              effort_2, effort_3, effort_4) %>%
  group_by(subjectid) %>%
  filter(completed == 1) %>%
  mutate(Domain = "Speech")

NASA.effort <- rbind(NASA.effort.wm,NASA.effort.speech) %>% select(-completed) %>%
  pivot_longer(names_to = "effort", values_to = "rating", -c(subjectid,Domain)) %>%
  separate(col = effort, into=c(NA,"Task"), sep = "_") %>%
    mutate(taskCode = factor(Task, levels=c(1,2,3,4), labels=c(0,1,2,3)),
          domainCode = factor(Domain, levels = c("WM","Speech"), labels = c(0,1)))
NASA.effort$taskCode <- as.numeric(NASA.effort$taskCode)
NASA.effort$domainCode <- as.numeric(NASA.effort$domainCode)

m.Effort <- brm(data = NASA.effort, rating ~ taskCode*domainCode + (1 | subjectid),
                file = "models/m.Effort.rds")
summary(m.Effort)
```

```
##  Family: gaussian
```

```
##   Links: mu = identity; sigma = identity
## Formula: rating ~ taskCode * domainCode + (1 | subjectid)
##    Data: NASA.effort (Number of observations: 856)
##   Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup draws = 4000
##
## Group-Level Effects:
## ~subjectid (Number of levels: 107)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     2.79      0.23     2.37     3.27 1.00     1025     1820
##
## Population-Level Effects:
##                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept               6.39      0.92     4.57     8.19 1.00     1940     2231
## taskCode                2.52      0.32     1.89     3.16 1.00     2037     2493
## domainCode              2.55      0.56     1.46     3.67 1.00     2051     2209
## taskCode:domainCode    -0.33      0.21    -0.74     0.07 1.00     2004     2224
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     3.32      0.09     3.16     3.50 1.00     4039     3217
##
## Draws were sampled using sampling(NUTS). 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).
```

```r
NASA_effort_sum <- summarySEwithin2(NASA.effort, measurevar = "rating",
                                    withinvars = c("Task","Domain"), idvar = "subjectid")
NASA_effort_sum$Task <- factor(NASA_effort_sum$Task, levels = c(1,2,3,4),
                               labels = c("black","red","blue","purple"))

p.effort <- ggplot(NASA_effort_sum, aes(x=Task, y=rating, fill=Domain)) +
  theme(plot.title = element_text(hjust = 0.5), panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(), panel.background = element_blank(),
        axis.line = element_line(colour = "black")) +
  geom_bar(stat="identity", position=position_dodge()) +
  geom_errorbar(position=position_dodge(width=0.9), aes(ymin=rating-ci, ymax=rating+ci), width=.2) +
  xlab("Task") + ylab("Effort") + ggtitle("Self-Reported Effort")
p.effort + labs(fill = "Domain") + scale_fill_brewer(palette = "Paired")
```


Self−Reported Effort
Effort
20
15
10
5
0
black
red
blue
purple
Task
Domain
Speech
WM