Duration reproduction under memory pressure

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1 Load packages and functions and data

1.1 mean reproduction biases and working memory performance

Calculate mean reproduction biases and working memory performance for each experiment.

```
# mean reproduction biases
mRep = ExpData %>% group_by(ExpName, NSub, WMSize, Load, gap, curDur) %>%
    summarise(m_bias = mean(bias), se_bias = sd(bias)/sqrt(n()), n = n())

# general bias
mBias = mRep %>% group_by(ExpName, Load, gap, NSub) %>%
    summarise(ms_bias = mean(m_bias)*1000, se_bias = sd(m_bias)/sqrt(n())*1000)

# mean working memory performance
mWM = ExpData %>% group_by(ExpName, NSub, WMSize,gap, Load) %>%
    summarise(m_WMCrr = mean(WMCrr), se_WMCrr = sd(WMCrr)/sqrt(n()), n = n())
```

1.2 Central tendency effect

Next, we estimate the central tendency effect by using linear regression. First, we prepare several useful functions

```
# a simple linear model function

lm_model <- function(df) {
    lm(m_bias ~ curDur, data = df)
}

# obtain the estimates of the linear model

lm_estimate <- function(df) {
    df %>% group_by(ExpName, NSub, gap, Load) %>% nest() %>%
    mutate(lm = map(data, lm_model)) %>% # linear regression
    mutate(slope = map(lm, broom::tidy)) %>% # get estimates
    unnest(slope) %>% # remove raw data
    dplyr::select(-std.error,-statistic, -p.value) %>% # remove unnessary columns
    spread(term, estimate) %>% # spread stimates
    dplyr::rename(Intercept = `(Intercept)`, slope = curDur) %>% # rename columns
    mutate(cti = -slope) # central tendency index
}
```

```
# now estimate the central tendency effect
mRep_cti = mRep %>% lm_estimate()
```

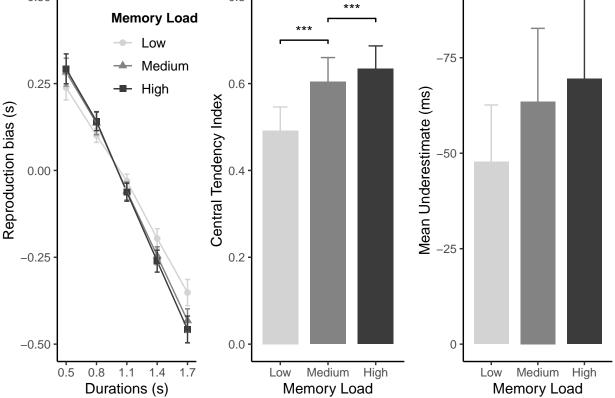
1.3 Plotting functions

```
#plot reproduction bias by duration and memory load (central tendency effect) based on mRep
plot cti <- function(data){</pre>
  # from subject-level to group-level
  data %>% group_by(Load, curDur) %>% summarise(mm_bias = mean(m_bias), se_bias = sd(m_bias)/sqrt(n()))
  ggplot(aes(curDur, mm_bias, color = Load, shape = Load)) +
    geom_point(size = 2, stat = 'identity') + geom_line() +
    geom_errorbar(aes(ymin = mm_bias - se_bias, ymax = mm_bias + se_bias), width = 0.05) +
    coord_cartesian(ylim = c(-0.5, 0.5)) +
    scale_x_continuous(breaks=c(0.5, 0.8, 1.1, 1.4, 1.7)) +
    labs(x="Durations (s)", y="Reproduction bias (s)",
       shape ="Memory Load", color = "Memory Load") +
   theme_new + greySet3 + theme(legend.position = c(.7,.8),
        legend.text = element_text(size = 10),
        legend.title = element_text(size = 10, face = "bold"),
        plot.title = element_text(hjust = 0.5))
}
# plot mean biases by memory load based on mBias
plot bias Load <- function(data){</pre>
  data %>% group_by(Load) %>% summarise(bias = mean(ms_bias), se_bias = sd(ms_bias)/sqrt(n())) %>%
  ggplot(aes(Load, bias, fill = Load)) +
    geom_bar(stat = 'identity', width = 0.75) +
    geom_errorbar(aes(ymin = bias - se_bias, ymax = bias + se_bias, color = Load), width = 0.3) +
    scale_y_reverse() +
    labs(x="Memory Load", y="Mean Underestimate (ms)", fill = "Memory Load", color = 'Memory Load') +
   theme_new + fillGreySet3 + greySet3 + theme(legend.position = "none",
        plot.title = element_text(hjust = 0.5))
}
# plot mean cti by memory load
plot_cti_Load <-function(data){</pre>
  data %>% group_by(Load) %>% summarise(m_cti = mean(cti), se_cti = sd(cti)/sqrt(n())) %>%
    ggplot(aes(Load, m_cti, fill = Load)) +
    geom_bar(stat = 'identity', width = 0.75) +
   geom_errorbar(aes(ymin = m_cti - se_cti, ymax = m_cti + se_cti, color = Load), width = 0.3) +
   labs(x="Memory Load", y="Central Tendency Index", fill = "Memory Load", color = "Memory Load") +
    theme_new + fillGreySet3 + greySet3 + theme(legend.position = "none",
        plot.title = element_text(hjust = 0.5))
}
# output three figures together
plot_fig <- function(Name, subfig = FALSE) {</pre>
  fig_a = mRep %>% filter(ExpName == Name) %>% plot_cti()
  fig_b = mRep_cti %>% filter(ExpName == Name) %>% plot_cti_Load()
  fig_c = mBias %>% filter(ExpName == Name) %>% plot_bias_Load()
  if(subfig) {
   return(list(fig_a=fig_a, fig_b=fig_b, fig_c=fig_c))
```

```
} else {
   plot_grid(fig_a, fig_b, fig_c, labels = c('a', 'b', 'c'), nrow = 1)
}
```

1.4 1. Working memory impacts on the encoding phase

```
# encoding manipulation
fig_encoding = plot_fig('Encoding', subfig = TRUE)
fig_encoding$fig_b = fig_encoding$fig_b +
  geom_signif(y_position = c(0.7, 0.75), xmin = c(1,2), xmax = c(2, 3), annotation = c("***", "***")) +
fig_en = plot_grid(fig_encoding$fig_a, fig_encoding$fig_b, fig_encoding$fig_c, labels = c('a', 'b', 'c'
# save figures
ggsave("./figures/fig_encoding.png", fig_en, width = 7, height = 3)
fig_en
                                                             C
а
                                 0.8
    0.50
                Memory Load
                 - Low
                                                                -75
                     Medium
    0.25
                                 0.6
                     High
```



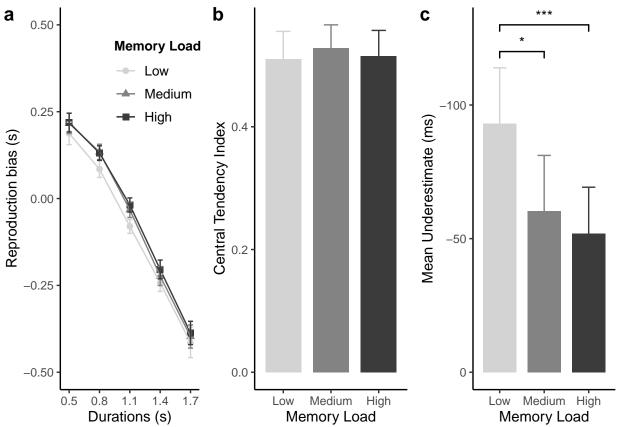
```
# rmANOVA on reproduction biases
av1 = mRep %>% filter(ExpName == 'Encoding') %>%
    ezANOVA(dv = m_bias, wid = NSub, within = .(curDur, Load), detailed = TRUE)
print(av1$ANOVA)
```

```
p p<.05
##
          Effect DFn DFd
                                 SSn
                                           SSd
                                                         F
## 1
          curDur
                      15 14.37532810 1.7788315 121.219980 1.389187e-08
            Load
                          0.02019136 0.2019869
                                                  1.499456 2.395105e-01
                      30
                          0.16147340 0.1187061 20.404175 2.544203e-06
## 3 curDur:Load
                   2
```

```
ges
## 1 0.872561859
## 2 0.009525504
## 3 0.071416868
#rmANOVA on cti
av2 = mRep_cti %>% filter(ExpName == 'Encoding') %>%
  ezANOVA(dv = cti, wid = NSub, within = Load, detailed = TRUE)
print(av2$ANOVA)
                               SSn
                                         SSd
                                                                 p p<.05
         Effect DFn DFd
## 1 (Intercept) 1 15 15.9725868 1.9764795 121.21998 1.389187e-08
## 2
           Load
                 2 30 0.1794149 0.1318957 20.40417 2.544203e-06
           ges
## 1 0.88339253
## 2 0.07842279
#rmANOVA on general bias
av3 = mBias %>% filter(ExpName == 'Encoding') %>%
 ezANOVA(dv = ms bias, wid = NSub, within = Load, detailed = TRUE)
print(av3$ANOVA)
                                                                p p<.05
         Effect DFn DFd
                               SSn
                                         SSd
                                                    F
## 1 (Intercept) 1 15 174392.655 211232.03 12.383964 0.003099731
           Load
                  2 30 4038.273 40397.39 1.499456 0.239510546
           ges
## 1 0.40935122
## 2 0.01579501
mWM %>% filter(ExpName == 'Encoding') %>% group_by(Load) %>% summarise(mean(m_WMCrr), sd(m_WMCrr)/sqrt(
## # A tibble: 3 x 3
    Load `mean(m_WMCrr)` `sd(m_WMCrr)/sqrt(n())`
##
    <fct>
                     <dbl>
                                             <dbl>
## 1 Low
                     0.899
                                            0.0100
                     0.724
## 2 Medium
                                            0.0228
                     0.664
## 3 High
                                            0.0206
mWM %>% filter(ExpName == 'Encoding') %>%
 ezANOVA(dv = m_WMCrr, wid = NSub, within = Load, detailed = TRUE)
## Warning: Converting "NSub" to factor for ANOVA.
## $ANOVA
         Effect DFn DFd
                             SSn
                                        SSd
                                                    F
                                                                 p p<.05
## 1 (Intercept) 1 15 27.90426 0.17549221 2385.08547 5.982001e-18
                  2 30 0.47617 0.07477734 95.51757 9.770098e-14
          Load
          ges
##
## 1 0.9911109
## 2 0.6554847
##
## $`Mauchly's Test for Sphericity`
## Effect W
                             p p<.05
## 2 Load 0.9782117 0.8570968
##
## $`Sphericity Corrections`
                           p[GG] p[GG]<.05 HFe
   Effect
                 GGe
                                                           p[HF] p[HF]<.05
## 2 Load 0.9786763 1.729369e-13
                                        * 1.123914 9.770098e-14
```

1.5 2. Working memory impacts on the reproduction phase

```
# reproduction manipulation
fig_reproduction = plot_fig('Reproduction', subfig = TRUE)
fig_reproduction$fig_c = fig_reproduction$fig_c +
    geom_signif(y_position = c(120, 130), xmin = c(1,1), xmax = c(2, 3), annotation = c("*", "***")) + yl
fig_rp = plot_grid(fig_reproduction$fig_a, fig_reproduction$fig_b, fig_reproduction$fig_c, labels = c(', # save figures)
ggsave("./figures/fig_reproduction.png", fig_rp, width = 7, height = 3)
fig_rp
```

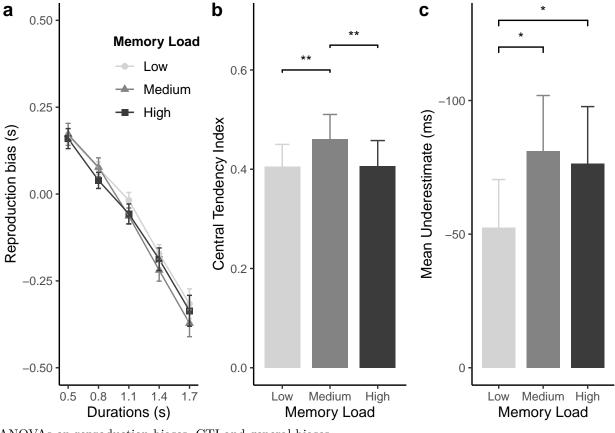


```
# rmANOVA on reproduction biases
av1 = mRep %>% filter(ExpName == 'Reproduction') %>%
  ezANOVA(dv = m_bias, wid = NSub, within = .(curDur, Load), detailed = TRUE)
print(av1$ANOVA)
##
          Effect DFn DFd
                                  SSn
                                              SSd
                                                                         p p<.05
## 1
          curDur
                      15 11.591282622 1.05861571 164.2420734 1.750724e-09
## 2
                      30
                         0.075134954 0.08926041 12.6262500 1.050848e-04
                   2
            Load
                      30
                          0.002401303 0.06627483
                                                    0.5434874 5.863297e-01
## 3 curDur:Load
##
## 1 0.905184705
## 2 0.058276409
## 3 0.001973859
```

```
#rmANOVA on cti
av2 = mRep_cti %>% filter(ExpName == 'Reproduction') %>%
  ezANOVA(dv = cti, wid = NSub, within = Load, detailed = TRUE)
print(av2$ANOVA)
##
         Effect DFn DFd
                                  SSn
                                            SSd
                                                          F
                                                                       p p<.05
## 1 (Intercept)
                  1 15 12.879202913 1.1762397 164.2420734 1.750724e-09
## 2
                  2 30 0.002668114 0.0736387
                                                  0.5434874 5.863297e-01
            Load
##
             ges
## 1 0.911538595
## 2 0.002130152
#rmANOVA on general bias
av3 = mBias %>% filter(ExpName == 'Reproduction') %>%
  ezANOVA(dv = ms_bias, wid = NSub, within = Load, detailed = TRUE)
print(av3$ANOVA)
         Effect DFn DFd
                               SSn
                                         SSd
                                                                 p p<.05
                  1 15 224994.05 261627.36 12.89969 0.0026712111
## 1 (Intercept)
                  2 30 15026.99 17852.08 12.62625 0.0001050848
##
            ges
## 1 0.44599777
## 2 0.05102432
# given the significant of memory load on general bias, we further conduct post hoc pairwise t-test
mBias %>% filter(ExpName == 'Reproduction') -> mBias_rp
pairwise.t.test(x = mBias_rp$ms_bias, g = mBias_rp$Load, paired = TRUE, p.adjust.method = 'holm')
## Pairwise comparisons using paired t tests
## data: mBias_rp$ms_bias and mBias_rp$Load
##
##
         Low
                 Medium
## Medium 0.0124 -
         0.0006 0.2376
## High
##
## P value adjustment method: holm
```

1.6 3. Working memory on both encoding and reproduction phases

```
# both manipulation
fig_both = plot_fig('Both', subfig = TRUE)
fig_both$fig_b = fig_both$fig_b +
    geom_signif(y_position = c(0.6, 0.65), xmin = c(1,2), xmax = c(2, 3), annotation = c("**", "**")) + y
fig_both$fig_c = fig_both$fig_c +
    geom_signif(y_position = c(120, 130), xmin = c(1,1), xmax = c(2, 3), annotation = c("*", "*")) + ylim
fig_bt = plot_grid(fig_both$fig_a, fig_both$fig_b, fig_both$fig_c, labels = c('a', 'b', 'c'), nrow = 1)
# save figures
ggsave("./figures/fig_both.png", fig_bt, width = 7, height = 3)
fig_bt
```



ANOVAs on reproduction biases, CTI and general biases

```
# rmANOVA on reproduction biases
av1 = mRep %>% filter(ExpName == 'Both') %>%
  ezANOVA(dv = m_bias, wid = NSub, within = .(curDur, Load), detailed = TRUE)
print(av1$ANOVA)
                                                                     p p<.05
##
          Effect DFn DFd
                                SSn
                                            SSd
                                                        F
## 1
          curDur
                      15 7.77070236 1.47269604 79.147721 2.273681e-07
## 2
            Load
                      30 0.03746856 0.07528366 7.465477 2.336867e-03
                      30 0.02979912 0.06209241 7.198734 2.795412e-03
##
  3 curDur:Load
##
            ges
## 1 0.82836469
## 2 0.02274212
## 3 0.01817162
#rmANOVA on cti
av2 = mRep_cti %>% filter(ExpName == 'Both') %>%
  ezANOVA(dv = cti, wid = NSub, within = Load, detailed = TRUE)
print(av2$ANOVA)
                                                                     p p<.05
          Effect DFn DFd
                                SSn
                                            SSd
                                                        F
## 1 (Intercept)
                   1 15 8.63411374 1.63632894 79.147721 2.273681e-07
## 2
                   2 30 0.03311013 0.06899157 7.198734 2.795412e-03
            Load
##
            ges
## 1 0.83506636
## 2 0.01904599
```

```
#rmANOVA on general bias
av3 = mBias %>% filter(ExpName == 'Both') %>%
  ezANOVA(dv = ms_bias, wid = NSub, within = Load, detailed = TRUE)
print(av3$ANOVA)
##
          Effect DFn DFd
                                SSn
                                           SSd
                                                       F
                                                                   p p<.05
## 1 (Intercept)
                  1 15 235369.803 273998.56 12.885276 0.002682227
## 2
                   2 30
                           7493.713 15056.73 7.465477 0.002336867
            Load
##
            ges
## 1 0.44881491
## 2 0.02526973
Post hoc pairwise t-test on general bias
mBias %>% filter(ExpName == 'Both') -> mBias_bt
pairwise.t.test(x = mBias_bt$ms_bias, g = mBias_bt$Load, paired = TRUE, p.adjust.method = 'holm')
  Pairwise comparisons using paired t tests
##
## data: mBias_bt$ms_bias and mBias_bt$Load
##
##
          Low
                Medium
## Medium 0.013 -
        0.039 0.428
## High
##
## P value adjustment method: holm
Post hoc pairwise t-test on cti
mRep_cti %>% filter(ExpName == 'Both') -> mRep_cti_bt
pairwise.t.test(x = mRep_cti_bt$cti, g = mRep_cti_bt$Load, paired = TRUE, p.adjust.method = 'holm')
##
##
  Pairwise comparisons using paired t tests
##
## data: mRep_cti_bt$cti and mRep_cti_bt$Load
##
                 Medium
##
         Low
## Medium 0.0097 -
         0.9564 0.0097
## High
## P value adjustment method: holm
```

1.7 4. Working memory on both encoding and reproduction phases with gap

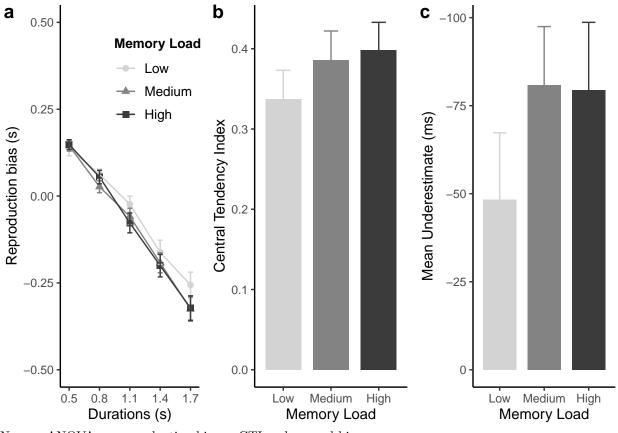
```
# both manipulation with gap
fig_a = mRep %>% filter(ExpName == 'Both_gap', gap == 1) %>% plot_cti() + #add text 'Short Gap' on the
  geom_text(aes(x = 0.8, y = 0.5, label = 'Short Gap'), size = 3, color = 'black') +
  theme(axis.title.x=element_blank(), axis.text.x=element_blank(), axis.ticks.x=element_blank(), legend
fig_b = mRep_cti %>% filter(ExpName == 'Both_gap', gap == 1) %>% plot_cti_Load() +
  theme(axis.title.x=element_blank(), axis.text.x=element_blank(), axis.ticks.x=element_blank())
fig_c = mBias %>% filter(ExpName == 'Both_gap', gap == 1) %>% plot_bias_Load()
```

```
fig_a2 = mRep %>% filter(ExpName == 'Both_gap', gap == 2) %>% plot_cti() + # remove legend
    geom_text(aes(x = 0.8, y = 0.5, label = 'Long Gap'), size = 3, color = 'black') +
  theme(legend.position = "none")
fig_b2 = mRep_cti %>% filter(ExpName == 'Both_gap', gap == 2) %>% plot_cti_Load()
fig_c2 = mBias %>% filter(ExpName == 'Both_gap', gap == 2) %>% plot_bias_Load()
# combine figures
fig_gap = plot_grid(fig_a, fig_b, fig_c, fig_a2, fig_b2, fig_c2, labels = c('a', 'b', 'c', 'd', 'e', 'f
# save figure
ggsave("./figures/fig_gap.png", fig_gap, width = 7, height = 6)
fig_gap
a
    0.50
                                  b
                                                                    Mean Underestimate (m®)
           Short C
                  Memory Load
                                  Central Tendency Index
                                     0.4
Reproduction bias (s)
                       Low
                                                                       -100
     0.25
                       Medium
                                     0.3
                       High
     0.00
                                                                        -50
                                     0.2
    -0.25
                                     0.1
                                                                               Low Medium High
    -0.50
                                     0.0
                                                                                Memory Load
Reproduction bias (s)
    0.50
           Long Gap
                                                                   Mean Underestimate (ms)
                                  Central Tendency Inde®
                                     0.5
                                                                       -150
                                     0.4
     0.25
                                                                       -100
                                     0.3
     0.00
                                     0.2
                                                                        -50
    -0.25
                                     0.1
    -0.50
                                     0.0
                                                                          0
                                                                                   Medium High
         0.5
              8.0
                  1.1
                        1.4
                                            Low
                                                 Medium High
                                                                               Low
              Durations (s)
                                                                                Memory Load
                                              Memory Load
ANOVAs on reproduction biases, CTI and general biases
# rmANOVA on reproduction biases
av1 = mRep %>% filter(ExpName == 'Both_gap') %>% mutate(gap = as.factor(gap)) %>%
  ezANOVA(dv = m_bias, wid = NSub, within = .(curDur, Load, gap), detailed = TRUE)
print(av1$ANOVA)
##
               Effect DFn DFd
                                          SSn
                                                       SSd
                                                                      F
                                                                                    p p<.05
## 1
               curDur
                             15 14.769798631 2.33210332 94.9987841 6.995472e-08
## 2
                  Load
                          2
                                 0.335512188 0.50079354 10.0494165 4.564620e-04
                                 0.002752928 0.10622926
                                                            0.3887246 5.423358e-01
## 3
                   gap
                          1
                             15
## 4
          curDur:Load
                          2
                             30
                                 0.081758356 0.13899499
                                                            8.8231620 9.691206e-04
## 5
                                 0.064638396 0.07475635 12.9698135 2.618334e-03
           curDur:gap
                          1
                             15
                                 0.011958925 0.05465190
                                                            3.2822990 5.139333e-02
## 6
                          2
                             30
             Load:gap
                          2
                                 0.001681400 0.04016814 0.6278857 5.405869e-01
## 7 curDur:Load:gap
                             30
##
               ges
```

```
## 1 0.8197475677
## 2 0.0936345392
## 3 0.0008469375
## 4 0.0245560716
## 5 0.0195144449
## 6 0.0036687686
## 7 0.0005174528
#rmANOVA on cti
av2 = mRep_cti %>% filter(ExpName == 'Both_gap') %>%mutate(gap = as.factor(gap)) %>%
  ezANOVA(dv = cti, wid = NSub, within = .(Load, gap), detailed = TRUE)
print(av2$ANOVA)
##
          Effect DFn DFd
                                  SSn
                                             SSd
                                                           F
                                                                        p p<.05
                   1 15 16.410887368 2.59122591 94.9987841 6.995472e-08
## 1 (Intercept)
                      30 0.090842618 0.15443888 8.8231620 9.691206e-04
## 2
            Load
                   2
## 3
                   1 15 0.071820440 0.08306261 12.9698135 2.618334e-03
             gap
## 4
                      30 0.001868222 0.04463127 0.6278857 5.405869e-01
        Load:gap
##
## 1 0.8509996882
## 2 0.0306465754
## 3 0.0243857632
## 4 0.0006497652
#rmANOVA on general bias
av3 = mBias %% filter(ExpName == 'Both_gap') %>% mutate(gap = as.factor(gap)) %>%
  ezANOVA(dv = ms_bias, wid = NSub, within = .(Load, gap), detailed = TRUE)
print(av3$ANOVA)
##
          Effect DFn DFd
                                 SSn
                                           SSd
                                                         F
                                                                      p p<.05
## 1 (Intercept)
                      15 946497.0875 642354.82 22.1022024 0.0002839936
                   1
            Load
                         67102.4377 100158.71 10.0494165 0.0004564620
## 3
                      15
                            550.5857 21245.85 0.3887246 0.5423357620
             gap
## 4
                      30
                           2391.7851 10930.38 3.2822990 0.0513933324
        Load:gap
##
              ges
## 1 0.5499095509
## 2 0.0797137793
## 3 0.0007102129
## 4 0.0030779074
```

2 5. working memory on encoding 2 (within-subject design)

```
# encoding manipulation
fig_encoding2 = plot_fig('Encoding2')
fig_encoding2
```

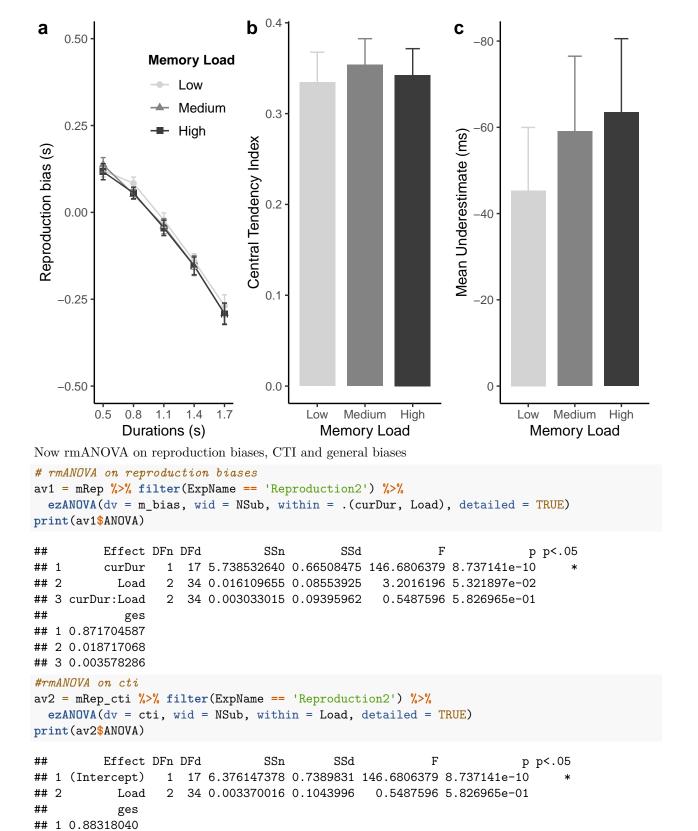


```
# rmANOVA on reproduction biases
av1 = mRep %>% filter(ExpName == 'Encoding2') %>%
  ezANOVA(dv = m_bias, wid = NSub, within = .(curDur, Load), detailed = TRUE)
print(av1$ANOVA)
                                                                       p p<.05
##
          Effect DFn DFd
                                 SSn
                                            SSd
                                                         F
## 1
          curDur
                      17 6.79976474 0.97028396 119.136259 4.227922e-09
## 2
            Load
                      34 0.06111974 0.25564376
                                                  4.064389 2.613973e-02
                      34 0.03415354 0.06270192
                                                  9.259845 6.161196e-04
##
  3 curDur:Load
##
            ges
## 1 0.84068165
## 2 0.04528229
## 3 0.02581945
#rmANOVA on cti
av2 = mRep_cti %>% filter(ExpName == 'Encoding2') %>%
  ezANOVA(dv = cti, wid = NSub, within = Load, detailed = TRUE)
print(av2$ANOVA)
                                                                      p p<.05
          Effect DFn DFd
                                 SSn
                                           SSd
                                                        F
                   1 17 7.55529416 1.0780933 119.136259 4.227922e-09
## 1 (Intercept)
## 2
                   2 34 0.03794837 0.0696688
                                                 9.259845 6.161196e-04
            Load
##
            ges
## 1 0.86811965
## 2 0.03200475
```

```
#rmANOVA on general bias
av3 = mBias %>% filter(ExpName == 'Encoding2') %>%
  ezANOVA(dv = ms_bias, wid = NSub, within = Load, detailed = TRUE)
print(av3$ANOVA)
         Effect DFn DFd
                                                     F
                                                                  p p<.05
                               SSn
                                         SSd
## 1 (Intercept)
                  1 17 261276.85 255606.60 17.377120 0.000643839
                   2 34 12223.95 51128.75 4.064389 0.026139730
## 2
            Load
##
            ges
## 1 0.45998457
## 2 0.03832448
Post hoc pairwise t-test on general bias
mBias %>% filter(ExpName == 'Encoding2') -> mBias_rp
pairwise.t.test(x = mBias_rp$ms_bias, g = mBias_rp$Load, paired = TRUE, p.adjust.method = 'holm')
   Pairwise comparisons using paired t tests
##
## data: mBias_rp$ms_bias and mBias_rp$Load
##
##
         Low
               Medium
## Medium 0.077 -
        0.151 0.848
## High
##
## P value adjustment method: holm
Post hoc pariwise t-test on cti
mRep_cti %>% filter(ExpName == 'Encoding2') -> mRep_cti_rp
pairwise.t.test(x = mRep_cti_rp$cti, g = mRep_cti_rp$Load, paired = TRUE, p.adjust.method = 'holm')
   Pairwise comparisons using paired t tests
##
## data: mRep_cti_rp$cti and mRep_cti_rp$Load
##
         Low
                 Medium
## Medium 0.0032 -
## High
         0.0015 0.4935
## P value adjustment method: holm
```

3 6. working memory on reproduction 2 (within-subject design)

```
# reproduction manipulation
fig_reproduction2 = plot_fig('Reproduction2')
fig_reproduction2
```

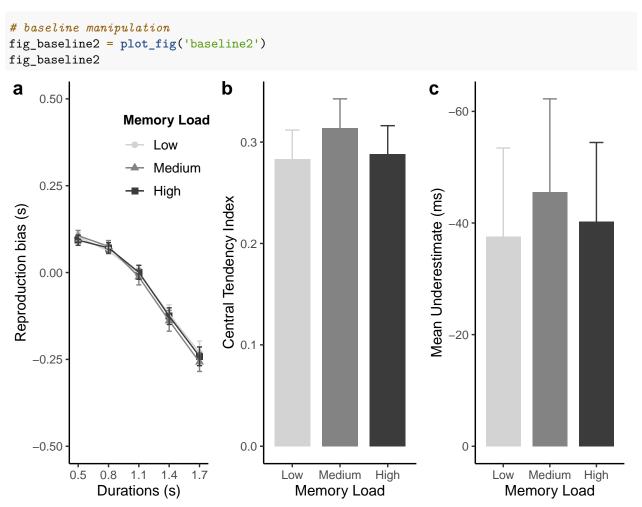


2 0.00397993

```
#rmANOVA on general bias
av3 = mBias %>% filter(ExpName == 'Reproduction2') %>%
  ezANOVA(dv = ms_bias, wid = NSub, within = Load, detailed = TRUE)
print(av3$ANOVA)
##
                                           SSd
                                                      F
                                                                   p p<.05
          Effect DFn DFd
                                 SSn
## 1 (Intercept)
                      17 169106.747 230592.43 12.46708 0.002566336
## 2
            Load
                   2
                      34
                           3221.931 17107.85 3.20162 0.053218967
##
            ges
## 1 0.40571952
## 2 0.01284036
```

Results showed only the main effect of Duration. Memory loads were marginal...

4 7. working memory on baseline 2 (within-subject design)



```
# rmANOVA on reproduction biases
av1 = mRep %>% filter(ExpName == 'baseline2') %>%
    ezANOVA(dv = m_bias, wid = NSub, within = .(curDur, Load), detailed = TRUE)
print(av1$ANOVA)
```

```
Effect DFn DFd
                                                                     p p<.05
                                SSn
                                           SSd
## 1
                 1 17 4.233692214 0.61651895 116.740560 4.922194e-09
         curDur
## 2
           Load
                 2 34 0.002916080 0.04861866 1.019637 3.714917e-01
                 2 34 0.008762427 0.04946308 3.011564 6.249625e-02
## 3 curDur:Load
            ges
## 1 0.855586420
## 2 0.004064129
## 3 0.012113456
#rmANOVA on cti
av2 = mRep_cti %>% filter(ExpName == 'baseline2') %>%
 ezANOVA(dv = cti, wid = NSub, within = Load, detailed = TRUE)
print(av2$ANOVA)
         Effect DFn DFd
                               SSn
                                          SSd
                                                       F
                                                                    p p<.05
                  1 17 4.70410246 0.68502106 116.740560 4.922194e-09
## 1 (Intercept)
                  2 34 0.00973603 0.05495898
                                                3.011564 6.249625e-02
           Load
           ges
## 1 0.86407626
## 2 0.01298629
#rmANOVA on general bias
av3 = mBias %>% filter(ExpName == 'baseline2') %>%
 ezANOVA(dv = ms_bias, wid = NSub, within = Load, detailed = TRUE)
print(av3$ANOVA)
                                                                p p<.05
         Effect DFn DFd
                               SSn
                                          SSd
                                                     F
## 1 (Intercept)
                 1 17 91376.2002 213761.839 7.266944 0.01531098
## 2
           Load
                  2 34
                          583.2161
                                     9723.731 1.019637 0.37149172
##
            ges
## 1 0.290210527
## 2 0.002602844
```

Only the main effect of Duration was significant.