Demographic and Behavioral Data Analysis

Setup

```r
# load packages

packages <- c("here","dplyr","ggplot2","ppcor","tidyverse","nlme","multcomp",
          "effectsize", "xlsx","effectsize")
lapply(packages, library, character.only = TRUE)
```

Load data

```r
variables_all <- read.table(here("data/variables_TD_N50.txt"),
                 sep = "\t", header = T)
posttest_long <- read.table(here("data/posttest_N50.txt"), header = T)
```

Demographic information

```r
# gender
table(variables_all$gender[!duplicated(variables_all$Subject)])
```

```
##
##  1  2
## 30 20
```

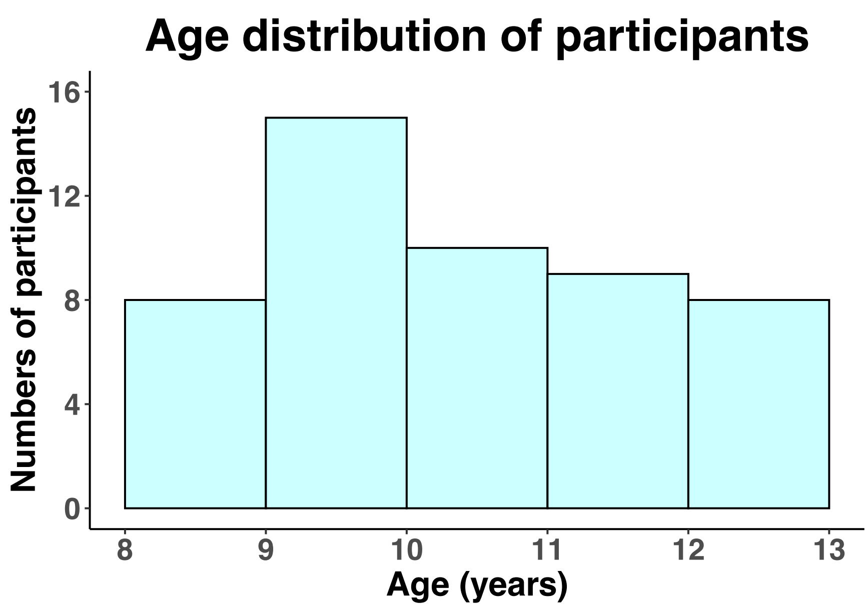
```r
# age, mean FD
variables_all[!duplicated(variables_all$Subject),] %>%
    summarise(mean(age),sd(age),max(age),min(age), mean(mean_FD),
          sd(mean_FD),max(mean_FD),min(mean_FD))
```

```
##   mean(age)  sd(age) max(age) min(age) mean(mean_FD) sd(mean_FD) max(mean_FD)
## 1   10.3822 1.332384    12.97     8.18       0.22786  0.07765465        0.417
##   min(mean_FD)
## 1        0.096
```

```r
# correlation between age and mean FD

rr <- cor.test(variables_all$age[!duplicated(variables_all$Subject)],
     variables_all$mean_FD[!duplicated(variables_all$Subject)])

r_to_d(rr$estimate)
```

```
##        cor
## -0.4995558
```

```
## plots
# age distribution
ggplot(variables_all[!duplicated(variables_all$Subject),], aes(x=age)) +
    geom_histogram(binwidth = 1,boundary = 0, closed = "left",
                   colour="black",fill="#CCFFFF") +
    theme(panel.background = element_blank(),
          axis.line = element_line(colour = "black")) +
    scale_y_continuous(breaks=seq(0, 16, 4),limits = c(0,16)) +
    scale_x_continuous(breaks=seq(8, 13, 1),limits = c(8,13)) +
    labs(x = "Age (years)", y = "Numbers of participants") +
    theme(axis.text = element_text(size = 16, face = "bold"),
          axis.title = element_text(size = 18, face = "bold") ) +
    ggtitle("Age distribution of participants") +
    theme(plot.title = element_text(hjust = 0.5),
          text = element_text(size = 20, face = "bold"))
```



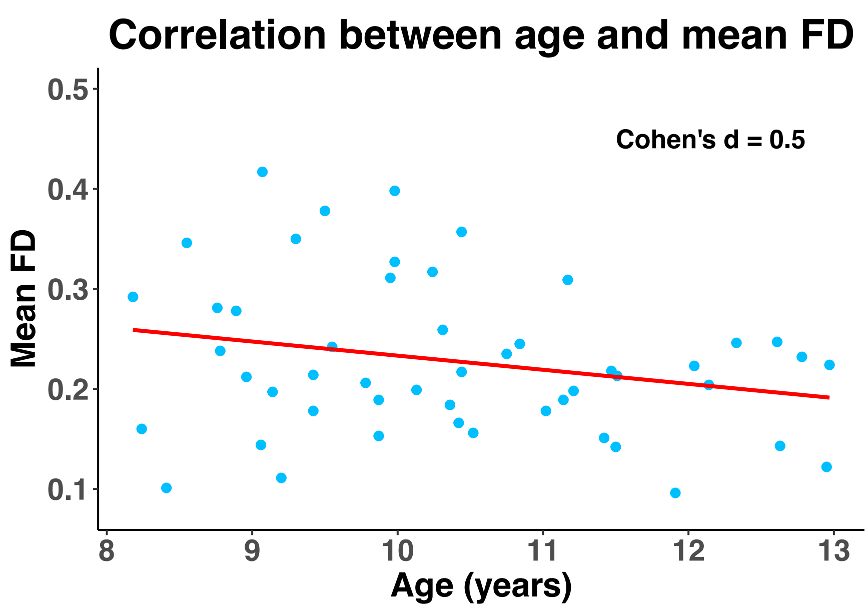

```
# plots for age and mean FD
r_to_d(rr$estimate)
```

```
##        cor
## -0.4995558
```

```
ggplot(variables_all[!duplicated(variables_all$Subject),],
       aes(x=age, y = mean_FD)) +
    geom_point(color = "deepskyblue1", size = 2) +
    geom_smooth(method=lm,se=F,color = "red",fullrange = T) +
    labs(x = "Age (years)", y = "Mean FD", title = "Correlation between age and mean FD") +
    scale_y_continuous(breaks=seq(0.0,0.5,0.1),limits = c(0.08,0.5)) +
    theme(panel.background = element_blank(),
          axis.line = element_line(colour = "black")) +
```

```
    theme(axis.text = element_text(size = 16, face = "bold"),
          axis.title = element_text(size = 18, face = "bold") ) +
     annotate("text", x=11.5,y=.45, label = "Cohen's d = 0.5",
              hjust=0,size = 5, fontface = "bold") +
    theme(plot.title = element_text(hjust = 0.5),
          text = element_text(size = 18, face ="bold"))
```

```
## `geom_smooth()` using formula 'y ~ x'
```



ethnicity, race, and income

```
demog_cmnt <- read.xlsx(here("data/demog_cmnt.xlsx"),sheetIndex = 1)
demog_cat <- read.csv(here("data/demog_CAT.csv"))

    demog_cmnt_new <- demog_cmnt[demog_cmnt$Participant %in%
                variables_all$Subject[!duplicated(variables_all$Subject)],
            c("Participant","X3..Ethnicity","X4..Race","X15..Household.Income")]

    colnames(demog_cmnt_new) <- c("subjectid", "ethnicity", "race", "income")

    demog_cat_new <- demog_cat[demog_cat$RED_ID %in%
                   variables_all$Subject[!duplicated(variables_all$Subject)],
                   c("RED_ID","ethnicity","race","income")]
# ethnicity
demog_cat_new$Ethnicity[demog_cat_new$ethnicity == "Not Hispanic or Latino"] <- "Not Hispanic/Latino"
demog_cat_new$Ethnicity[demog_cat_new$ethnicity == "Hispanic or Latino"] <- "Hispanic/Latino"
demog_cat_new$Ethnicity[demog_cat_new$ethnicity == "Does not wish to disclose"] <- "Unknown"

colnames(demog_cat_new)[1] <- c("subjectid")
head(demog_cat_new)
```

```
##      subjectid              ethnicity
## 1  RED_CAT_112 Not Hispanic or Latino
## 2  RED_CAT_123 Not Hispanic or Latino
## 5  RED_CAT_124     Hispanic or Latino
## 6  RED_CAT_118 Not Hispanic or Latino
## 11 RED_CAT_133 Not Hispanic or Latino
## 12 RED_CAT_150 Not Hispanic or Latino
##                                                          race
## 1  American Indian or Alaskan Native,Black or African American
## 2                               Black or African American,Asian
## 5                                            White or Caucasian
## 6                                            White or Caucasian
## 11                                           White or Caucasian
## 12                                           White or Caucasian
##                         income          Ethnicity
## 1  more than $75,000 per year Not Hispanic/Latino
## 2  more than $75,000 per year Not Hispanic/Latino
## 5  more than $75,000 per year     Hispanic/Latino
## 6  more than $75,000 per year Not Hispanic/Latino
## 11 more than $75,000 per year Not Hispanic/Latino
## 12 more than $75,000 per year Not Hispanic/Latino
```

```
demog_cmnt_new$Ethnicity[demog_cmnt_new$ethnicity == "N"] <- "Not Hispanic/Latino"
demog_cmnt_new$Ethnicity[demog_cmnt_new$ethnicity == "H"] <- "Hispanic/Latino"

# race
demog_cat_new$Race[demog_cat_new$race == "Asian,White or Caucasian" |
            demog_cat_new$race == "American Indian or Alaskan Native,Black or African American"|
            demog_cat_new$race == "Black or African American,White or Caucasian" |
            demog_cat_new$race == "Black or African American,Asian"] <- "more than one race"
demog_cat_new$Race[demog_cat_new$race == "White or Caucasian"] <- "White/Caucasian"
demog_cat_new$Race[demog_cat_new$race == "Black or African American"] <- "Black/African American"

demog_cmnt_new$Race <- demog_cmnt_new$race
demog_cmnt_new$Race[demog_cmnt_new$race == "W"] <- "White/Caucasian"
demog_cmnt_new$Race[demog_cmnt_new$race == "B"] <- "Black/African American"
demog_cmnt_new$Race[demog_cmnt_new$race == "A, W" |
                demog_cmnt_new$race == "B, W"  ] <- "more than one race"

# income
demog_cmnt_new$Income <- demog_cmnt_new$income
demog_cmnt_new$Income[demog_cmnt_new$income == "7"] <- ">75k"
demog_cmnt_new$Income[demog_cmnt_new$income == "6"] <- "65k-75k"
demog_cmnt_new$Income[demog_cmnt_new$income == "4"] <- "45k-55k"
demog_cmnt_new$Income[is.na(demog_cmnt_new$income)] <- "Unknown"

demog_cat_new$Income[demog_cat_new$income == "more than $75,000 per year"] <- ">75k"
demog_cat_new$Income[demog_cat_new$income == "$15, 000-$25, 000 per year"] <- "15k-25k"
demog_cat_new$Income[demog_cat_new$income == "$35, 000-$45, 000 per year"] <- "35k-45k"
demog_cat_new$Income[demog_cat_new$income == ""] <- "Unknown"

demog_all <- rbind.data.frame(demog_cmnt_new[,c("subjectid","Ethnicity", "Race", "Income")],
                  demog_cat_new[,c("subjectid","Ethnicity", "Race","Income")])
```

```r
demog_all$Ethnicity <- factor(demog_all$Ethnicity, levels = c("Not Hispanic/Latino",
                                   "Hispanic/Latino", "Unknown"))
demog_all$Race <- factor(demog_all$Race, levels = c("White/Caucasian","Black/African American",
                             "more than one race"))
demog_all$Income <- factor(demog_all$Income, levels = c(">75k","65k-75k","45k-55k",
                             "35k-45k","15k-25k","Unknown"))

a <- table(demog_all$Ethnicity)
b <- table(demog_all$Race)
inc <- table(demog_all$Income)
print(paste0((a["Hispanic/Latino"]/50)*100,"% as Hispanic/Latino"))
```

```
## [1] "10% as Hispanic/Latino"
```

```r
print(paste0((b["White/Caucasian"]/50)*100,"% as White/Caucasian"))
```

```
## [1] "60% as White/Caucasian"
```

```r
print(paste0((b["Black/African American"]/50)*100,"% as Black/African American"))
```

```
## [1] "22% as Black/African American"
```

```r
print(paste0((b["more than one race"]/50)*100,"% as more than one race"))
```

```
## [1] "18% as more than one race"
```

```r
print(paste0((inc[">75k"]/50)*100,"% reporting over $75,000 in total family income"))
```

```
## [1] "86% reporting over $75,000 in total family income"
```

```r
print(paste0(((inc["65k-75k"] + inc["45k-55k"] + inc["35k-45k"])/50)*100,
         "% reporting family income between $35,000-$75,000"))
```

```
## [1] "6% reporting family income between $35,000-$75,000"
```

```r
print(paste0((inc["15k-25k"]/50)*100, "% reporting family income between $35,000-$75,000"))
```

```
## [1] "4% reporting family income between $35,000-$75,000"
```

```r
print(paste0((inc["Unknown"]/50)*100, "% did not report on income"))
```

```
## [1] "4% did not report on income"
```

In-scanner performance

```r
# mean RT and accuracy
variables_all %>%
    summarise(mean(RT),sd(RT),mean(ACC_per), sd(ACC_per))
```

```
##   mean(RT)    sd(RT) mean(ACC_per) sd(ACC_per)
## 1 2.043435 0.3197043      90.16661     7.49084
```

```r
# regression analysis on RT
anova(lme(RT ~ social*age + mental +  gender + mean_FD + IQ,
      random = ~1|Subject,
      data = variables_all))
```

```
##             numDF denDF  F-value p-value
## (Intercept)     1   147 3449.402  <.0001
## social          1   147   27.080  <.0001
## age             1    45   27.059  <.0001
## mental          1   147    0.339  0.5614
## gender          1    45    1.430  0.2380
## mean_FD         1    45    0.167  0.6852
## IQ              1    45    1.718  0.1966
## social:age      1   147    0.163  0.6872
```

```r
# post-hoc analysis on RT: mean RT of collapsed conditions between Peer vs. Character condition
beha <- as.data.frame(matrix(0,100,0))
beha$subj <- rep(variables_all$Subject[!duplicated(variables_all$Subject)],2)
beha$social <- rep(c("P","C"),each = 50)
beha$RT <- c((variables_all[variables_all$MentalState == "PM","RT"] +
    variables_all[variables_all$MentalState == "PNM","RT"])/2,
    (variables_all[variables_all$MentalState == "CM","RT"] +
        variables_all[variables_all$MentalState == "CNM","RT"])/2)

tt0 <- t.test(beha[beha$social == "P","RT"],beha[beha$social == "C","RT"],
          paired = T)

print(paste0("Peer vs. Character differences = ", round(tt0$estimate[1],2)))
```

```
## [1] "Peer vs. Character differences = -0.08"
```

```r
print(paste0("t=", round(tt0$statistic,1), " p=",round(tt0$p.value,5)))
```

```
## [1] "t=-4.7 p=2e-05"
```

```r
# regression analysis on accuracy
anova(lme(ACC_per ~ social*age + mental + gender + mean_FD + IQ,
      random = ~1|Subject,
      data = variables_all))
```

```
##             numDF denDF   F-value p-value
## (Intercept)     1   147 23396.459  <.0001
## social          1   147     2.042  0.1551
```

```
## age              1    45     1.770  0.1900
## mental           1   147     3.277  0.0723
## gender           1    45     0.042  0.8386
## mean_FD          1    45     2.487  0.1218
## IQ               1    45    24.331  <.0001
## social:age       1   147     5.818  0.0171
```

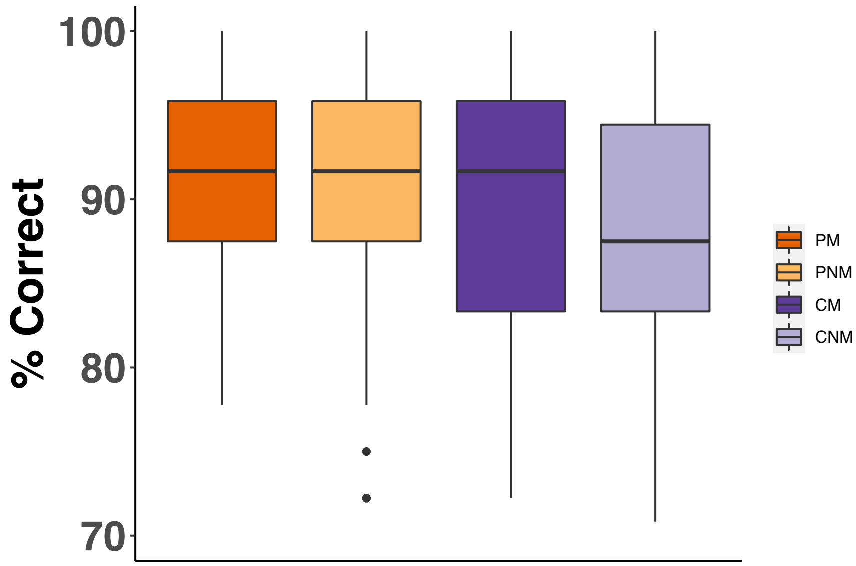
```r
anova(lme(ACC_per ~ age + mental + gender + mean_FD + IQ,
      random = ~1|Subject,
      data = variables_all[variables_all$social == "C",]))
```

```
##             numDF denDF   F-value p-value
## (Intercept)     1    49 12940.761  <.0001
## age             1    45     5.460  0.0240
## mental          1    49     2.069  0.1566
## gender          1    45     0.509  0.4794
## mean_FD         1    45     0.392  0.5346
## IQ              1    45    13.133  0.0007
```

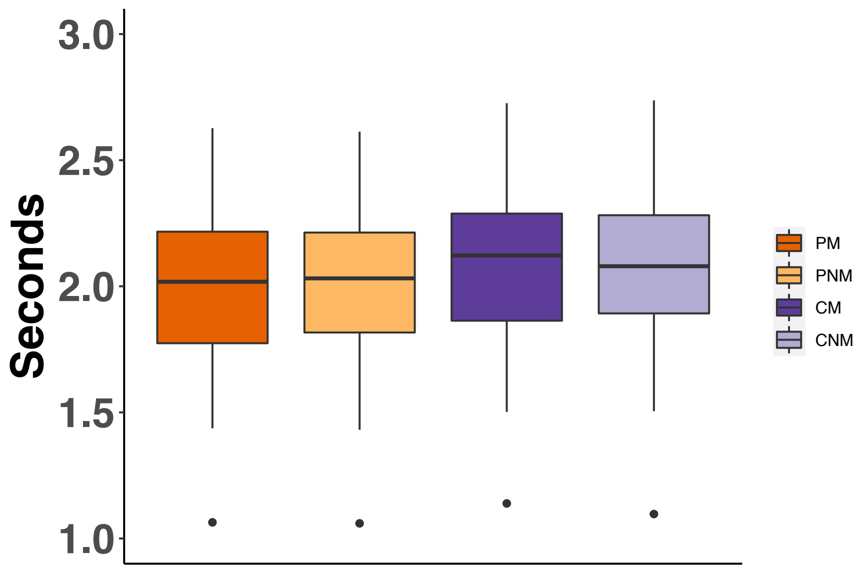
```r
anova(lme(ACC_per ~ age + mental + gender + mean_FD + IQ,
      random = ~1|Subject,
      data = variables_all[variables_all$social == "P",]))
```

```
##             numDF denDF   F-value p-value
## (Intercept)     1    49 18531.579  <.0001
## age             1    45     0.165  0.6869
## mental          1    49     1.220  0.2747
## gender          1    45     1.450  0.2349
## mean_FD         1    45     4.198  0.0463
## IQ              1    45    19.735  0.0001
```

```r
# boxplots
# function
boxplot_inscan <- function(data,x,y,n,beh,title) {
    p <- ggplot(data, aes_string(x, y, fill=x)) +
        geom_boxplot() +
        scale_fill_manual(values = c("#e66101","#fdb863","#5e3c99","#b2abd2")) +
        labs(y=beh, x="") +
        coord_cartesian(ylim = n)+
        theme(axis.text.x = element_blank(),
              axis.ticks.x = element_blank(),
              axis.text.y =element_text(size=22,face="bold"),
              axis.title.y =element_text(size=24,face="bold")) +
        theme(legend.title=element_blank()) +
        theme(panel.background = element_blank(),
              axis.line = element_line(colour = "black"))    #remove background
    print(p)
}

variables_all$MentalState <- factor(variables_all$MentalState,levels = c("PM","PNM","CM","CNM"))

boxplot_inscan(variables_all,"MentalState","ACC_per",c(70,100),c("% Correct"),c("Accuracy"))
```




```
boxplot_inscan(variables_all,"MentalState","RT",c(1,3),c("Seconds"),c("Reaction Time"))
```



Posttest questionnaire

```
# subjective reports assessed by the post-scan questionnaire
mean_P <- sapply(4:9,function(x) summary(posttest_long[posttest_long$social == "Peer",x]))
sd_P <- sapply(4:9,function(x) sd(posttest_long[posttest_long$social == "Peer",x]))
mean_C <- sapply(4:9,function(x) summary(posttest_long[posttest_long$social == "Character",x]))
sd_C <- sapply(4:9,function(x) sd(posttest_long[posttest_long$social == "Character",x]))

tt  <-  sapply(4:9,function(x) wilcox.test(posttest_long[posttest_long$social == "Peer",x],
```

```r
                        posttest_long[posttest_long$social == "Character",x],
                         paired = T))
```

```
## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with zeroes

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with zeroes

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with zeroes

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with zeroes

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with zeroes

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(posttest_long[posttest_long$social == "Peer", :
## cannot compute exact p-value with zeroes
```

```r
rownames(mean_P)
```

```
## [1] "Min."    "1st Qu." "Median"  "Mean"    "3rd Qu." "Max."
```

```r
reports <- as.data.frame(matrix(0, 6, 8))
colnames(reports) <- c("Measure","P.median","P.mean±sd","P.range","C.median",
               "C.mean±sd","C.range","PvsC")

for (i in 1:length(4:9)) {
    reports[i,1] <- colnames(posttest_long)[3+i]
```

```r
    reports[i,2:8] <- c(mean_P["Median",i], paste0(mean_P["Mean",i],"±",round(sd_P[i],2)),
                paste0(mean_P["Min.",i],"-",mean_P["Max.",i]),mean_C["Median",i],
                paste0(mean_C["Mean",i],"±",round(sd_C[i],2)),
                paste0(mean_C["Min.",i],"-",mean_C["Max.",i]),
                round(tt[,i]$p.value,4))
}

posttest <- c("like","likeguess","agreed","wantsee","attention","hardguess")

l <- match(posttest, reports[,1])

knitr::kable(reports[l,])
```

	Measure	P.median	P.mean±sd	P.range	C.median	C.mean±sd	C.range	PvsC
1	like	4.5	4.3±0.81	2–5	3	2.76±1.04	1–5	0
4	likeguess	4	3.84±0.96	1–5	3	3.26±1.12	1–5	9e-04
6	agreed	4	4.26±0.83	2–5	4	3.96±0.88	2–5	0.0312
5	wantsee	4	4.08±0.92	2–5	3	3.38±1.23	1–5	0
2	attention	4	3.9±0.91	1–5	3	3.4±0.97	1–5	0.0019
3	hardguess	2	2.38±1.23	1–5	2	2.2±1.29	1–5	0.3831

```r
## variability of subjective reports of enjoyment
# percent of subjects who rated 4 or 5 on Liked Chatting
k <- length(which(posttest_long$like[posttest_long$social == "Peer" ]>3))
(k/50)*100
```

```
## [1] 82
```

```r
# percent of  subjects who rated 4 or 5 when their answer matched the answer from the peer
k <- length(which(posttest_long$agreed[posttest_long$social == "Peer" ]>3))
(k/50)*100
```

```
## [1] 80
```

```r
# subjective reports when answering questions about the character
m <-  table(posttest_long$like[posttest_long$social == "Character" ])

(m/50)*100
```

```
##
##  1  2  3  4  5
## 12 24 48  8  8
```

```r
n <- as.numeric((m/50)*100)

print(paste0(n[1]+n[2],"% rated 1 or 2"))
```

```
## [1] "36% rated 1 or 2"
```

```r
print(paste0(n[3],"% rated 3"))
```

```
## [1] "48% rated 3"
```

```r
print(paste0(n[4]+n[5],"% rated 4 or 5"))
```

```
## [1] "16% rated 4 or 5"
```

```r
## regression analysis
posttest_long_new <- cbind.data.frame(posttest_long[rep(rownames(posttest_long),
                          each = 2),],
                variables_all[,c("gender","IQ","RT","ACC_per")])

# Liked Chatting
anova(lme(like ~ social*Age + gender + IQ, random = ~1|Subj,
      data = posttest_long_new))
```

```
##             numDF denDF   F-value p-value
## (Intercept)     1   148 1812.8649  <.0001
## social          1   148  184.7594  <.0001
## Age             1    46    0.4090  0.5257
## gender          1    46    3.0799  0.0859
## IQ              1    46    3.4820  0.0684
## social:Age      1   148    5.3481  0.0221
```

```r
# Liked Guessing
anova(lme(likeguess ~ social*Age + gender + IQ, random = ~1|Subj,
      data = posttest_long_new))
```

```
##             numDF denDF  F-value p-value
## (Intercept)     1   148 764.2427  <.0001
## social          1   148  46.4707  <.0001
## Age             1    46   0.0691  0.7939
## gender          1    46   1.9890  0.1652
## IQ              1    46   0.0009  0.9764
## social:Age      1   148   1.6897  0.1957
```

```r
# Felt When Matched
anova(lme(agreed~ social*Age + gender + IQ,random = ~1|Subj,
      data=posttest_long_new))
```

```
##             numDF denDF   F-value p-value
## (Intercept)     1   148 1719.8207  <.0001
## social          1   148   15.7241  0.0001
## Age             1    46    0.7294  0.3975
## gender          1    46    4.4194  0.0410
## IQ              1    46    0.0525  0.8197
## social:Age      1   148    0.5054  0.4783
```

```r
# Wanted to See
anova(lme(wantsee ~ social*Age + gender + IQ,random = ~1|Subj,
      data=posttest_long_new))
```

```
##             numDF denDF  F-value p-value
## (Intercept)     1   148 732.4956  <.0001
## social          1   148  81.3911  <.0001
## Age             1    46   1.1437  0.2904
## gender          1    46   1.0905  0.3018
## IQ              1    46   0.3131  0.5785
## social:Age      1   148   6.4771  0.0120
```

```r
# Paid Attention
anova(lme(attention ~ social*Age + gender + IQ,random = ~1|Subj,
      data = posttest_long_new))
```

```
##             numDF denDF   F-value p-value
## (Intercept)     1   148 1043.2729  <.0001
## social          1   148   39.1189  <.0001
## Age             1    46    0.0038  0.9514
## gender          1    46    1.1742  0.2842
## IQ              1    46    0.0032  0.9549
## social:Age      1   148   16.2993  0.0001
```

```r
# Perceived Difficulty
anova(lme(hardguess ~ social*Age + gender + IQ,random = ~1|Subj,
      data = posttest_long_new))
```

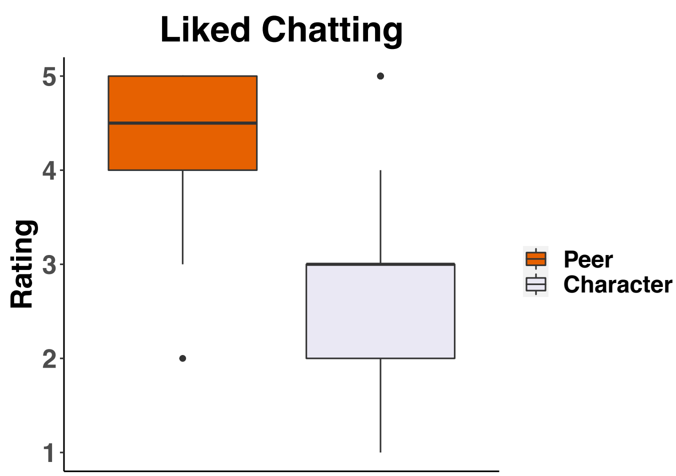
```
##             numDF denDF   F-value p-value
## (Intercept)     1   148 301.69708  <.0001
## social          1   148   3.27205  0.0725
## Age             1    46  14.66063  0.0004
## gender          1    46   0.53307  0.4690
## IQ              1    46   7.31968  0.0095
## social:Age      1   148   0.21180  0.6460
```

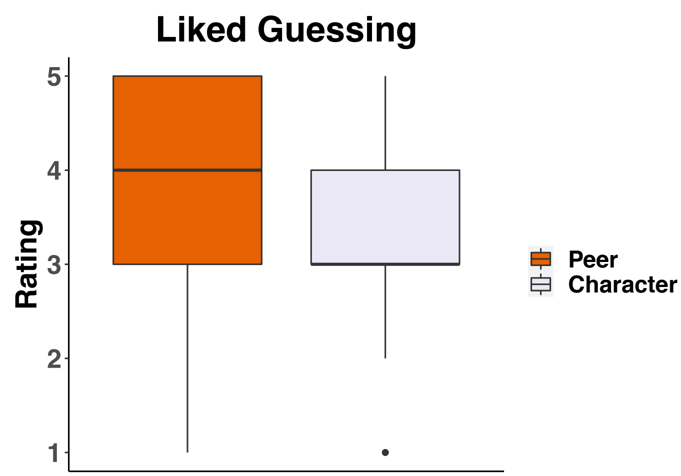
```r
# boxplots
measures <- c("like","likeguess","agreed","wantsee","attention","hardguess")
titles <- c("Liked Chatting","Liked Guessing","Felt When Matched","Wanted to See",
        "Paid Attention","Perceived Difficulty")

posttest_long$social <- factor(posttest_long$social,levels = c("Peer", "Character"))

summary(posttest_long$attention)
```

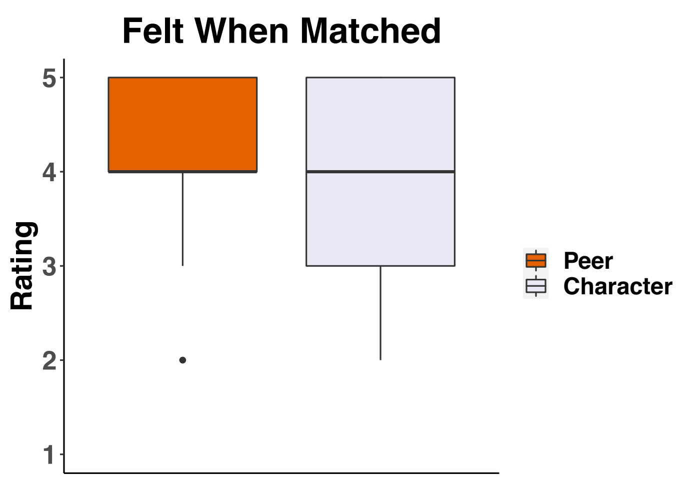
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    3.00    4.00    3.65    4.00    5.00
```

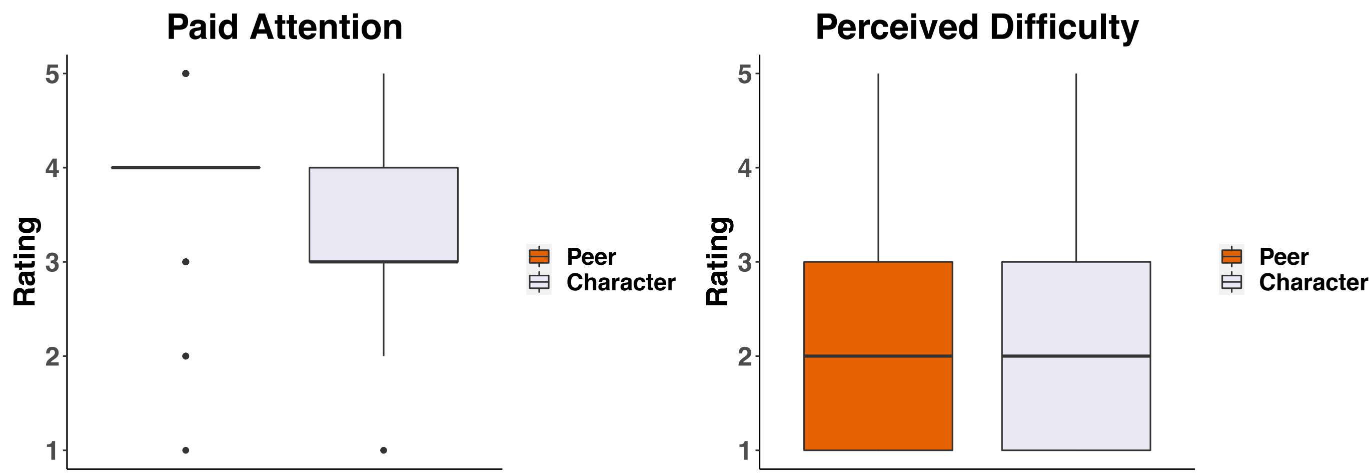
```r
for (i in 1:6) {
    p <- ggplot(posttest_long, aes_string(x="social",y=measures[i],fill = "social")) +
```

```
        geom_boxplot() +
        labs(y="Rating") +
        ggtitle(titles[i]) +
        theme(plot.title = element_text(hjust = 0.5),
              text = element_text(size = 20, face = "bold")) +
        theme(legend.title=element_blank()) +
        theme(axis.title.x = element_blank(),
              axis.ticks.x = element_blank(),
              axis.text.x = element_blank(),
              axis.title.y = element_text(face = "bold",size=20),
              axis.text.y = element_text(face = "bold",size=18)) +
        coord_cartesian(ylim = c(1,5)) +
        scale_fill_manual(values = c("#e66101", "#eae8f4"))+
        theme(panel.background = element_blank(),
              axis.line = element_line(colour = "black"))
    print(p)
}
```









Correlations between mean RT and scial motivation

```
# mean RT
RT_mean <- aggregate(variables_all$RT,by = list(variables_all$social,variables_all$Subj),
             FUN=mean)

Cor_RT_Social <- as.data.frame(matrix(0,5,3))

posttest <- c("like","likeguess","agreed","wantsee","attention")

for (i in 1:length(posttest)) {
    mytest_P <- cor.test(RT_mean$x[RT_mean$Group.1 == "P"], posttest_long[posttest_long$social == "Peer
     method = "spearman",alternative = "less")

    Cor_RT_Social[i,1] <- posttest[i]
    Cor_RT_Social[i,2:3] <- c(round(mytest_P$estimate,3),round(mytest_P$p.value,3))
}

colnames(Cor_RT_Social) <- c("","rho","p")
Cor_RT_Social[,1] <-  titles <- c("Liked Chatting","Liked Guessing","Felt When Matched",
                  "Wanted to See","Paid Attention")
knitr::kable(Cor_RT_Social)
```

	rho	p
Liked Chatting	-0.123	0.197
Liked Guessing	-0.065	0.327
Felt When Matched	-0.252	0.038
Wanted to See	-0.238	0.048
Paid Attention	-0.030	0.418

Functional Connectivity and Brain-Behavior Analysis

Setup

```r
# load packages
packages <- c("here","dplyr","ggplot2","ppcor","tidyverse","nlme","multcomp","xlsx")
lapply(packages, library, character.only = TRUE)
source(here("code/flm_FC.R"))
source(here("code/FC_scatterplot.R"))
```

Load data

```r
mean_networks_FC <- read.table(here("data/mean_networks_FC.txt"),header = T)

mean_control_FC <- read.table(here("data/mean_control_FC.txt"),header = T)

variables_all <- read.table(here("data/variables_TD_N50.txt"),sep = "\t", header = T)
```

Within vs. between network

```r
tmp0 <- as.data.frame(matrix(0,50,5))

tmp0$reward <- (mean_networks_FC$reward_FC[mean_networks_FC$conditions=="PM"] +
            mean_networks_FC$reward_FC[mean_networks_FC$conditions=="PNM"] +
            mean_networks_FC$reward_FC[mean_networks_FC$conditions=="CM"] +
            mean_networks_FC$reward_FC[mean_networks_FC$conditions=="CNM"])/4

tmp0$mentalizing <- (mean_networks_FC$mental_FC[mean_networks_FC$conditions=="PM"] +
            mean_networks_FC$mental_FC[mean_networks_FC$conditions=="PNM"] +
            mean_networks_FC$mental_FC[mean_networks_FC$conditions=="CM"] +
            mean_networks_FC$mental_FC[mean_networks_FC$conditions=="CNM"])/4

tmp0$between <- (mean_networks_FC$between_FC[mean_networks_FC$conditions=="PM"] +
                mean_networks_FC$between_FC[mean_networks_FC$conditions=="PNM"] +
                mean_networks_FC$between_FC[mean_networks_FC$conditions=="CM"] +
                mean_networks_FC$between_FC[mean_networks_FC$conditions=="CNM"])/4

# within vs. between: one-tailed paird t-tests
t.test(tmp0$reward,tmp0$between,alternative = "greater",paired = T)
```

```
##
```

```
##  Paired t-test
##
## data:  tmp0$reward and tmp0$between
## t = 2.1301, df = 49, p-value = 0.01911
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.004812021         Inf
## sample estimates:
## mean of the differences
##                  0.0226
```

```
t.test(tmp0$mentalizing,tmp0$between,alternative = "greater",paired = T)
```

```
##
##  Paired t-test
##
## data:  tmp0$mentalizing and tmp0$between
## t = 9.9618, df = 49, p-value = 1.143e-13
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.1341368       Inf
## sample estimates:
## mean of the differences
##                 0.16128
```

Regression analysis on within- and between-network connectivity

```
# the main effect of social interaction and interaction effects
flm_FC(mean_networks_FC, "mental_FC","Age")
```

```
## [[1]]
##     socialP         age    mentalNM      gender     mean_FD          IQ
##   62.957537    1.348847    1.000000    1.055093    1.104513    1.055296
## socialP:age
##   63.169124
##
## [[2]]
##                        Beta.CI P.value
## (Intercept)   1.089(0.27,1.91)   0.010
## socialP     -0.572(-0.95,-0.2)   0.003
## age         -0.037(-0.08,0.01)   0.121
## mentalNM    -0.042(-0.09,0.01)   0.085
## gender      -0.056(-0.16,0.05)   0.317
## mean_FD     -0.207(-0.92,0.51)   0.574
## IQ                    0(0,0)   0.869
## socialP:age   0.056(0.02,0.09)   0.003
##
## [[3]]
##             numDF denDF  F-value p-value
## (Intercept)     1   147 402.9090  <.0001
```

```
## social          1   147   0.2005  0.6550
## age             1    45   0.0173  0.8961
## mental          1   147   3.0033  0.0852
## gender          1    45   0.8307  0.3669
## mean_FD         1    45   0.3268  0.5704
## IQ              1    45   0.0277  0.8686
## social:age      1   147   9.4017  0.0026
##
## [[4]]
##             numDF denDF  F-value p-value
## (Intercept)     1    49 353.4319  <.0001
## age             1    45   1.4061  0.2419
## mental          1    49   3.9226  0.0533
## gender          1    45   1.1408  0.2912
## mean_FD         1    45   0.0300  0.8633
## IQ              1    45   0.4389  0.5110
##
## [[5]]
##             numDF denDF   F-value p-value
## (Intercept)     1    49 279.54489  <.0001
## age             1    45   1.68361  0.2011
## mental          1    49   0.62575  0.4327
## gender          1    45   0.31871  0.5752
## mean_FD         1    45   0.64806  0.4250
## IQ              1    45   0.77698  0.3827
```

```
flm_FC(mean_networks_FC, "reward_FC","Age")
```

```
## [[1]]
##     socialP         age    mentalNM      gender     mean_FD          IQ
##   62.957537    1.358689    1.000000    1.055093    1.104513    1.055296
## socialP:age
##   63.178966
##
## [[2]]
##                          Beta.CI P.value
## (Intercept)     1.197(0.46,1.93)   0.002
## socialP     -0.468(-0.81,-0.12)   0.009
## age            -0.041(-0.08,0)   0.057
## mentalNM     -0.019(-0.06,0.02)   0.393
## gender       -0.052(-0.15,0.04)   0.297
## mean_FD       -0.059(-0.7,0.58)   0.859
## IQ             -0.002(-0.01,0)   0.200
## socialP:age    0.045(0.01,0.08)   0.008
##
## [[3]]
##             numDF denDF   F-value p-value
## (Intercept)     1   147 272.90293  <.0001
## social          1   147   0.02038  0.8867
## age             1    45   0.30882  0.5812
## mental          1   147   0.73351  0.3931
## gender          1    45   0.98076  0.3273
## mean_FD         1    45   0.04733  0.8288
## IQ              1    45   1.69261  0.1999
```

```
## social:age      1   147   7.13054  0.0084
##
## [[4]]
##             numDF denDF   F-value p-value
## (Intercept)     1    49 196.37601  <.0001
## age             1    45   0.35632  0.5535
## mental          1    49   0.30902  0.5808
## gender          1    45   1.34190  0.2528
## mean_FD         1    45   0.29887  0.5873
## IQ              1    45   1.05798  0.3092
##
## [[5]]
##             numDF denDF   F-value p-value
## (Intercept)     1    49 272.03322  <.0001
## age             1    45   3.24737  0.0782
## mental          1    49   0.38858  0.5359
## gender          1    45   0.38085  0.5403
## mean_FD         1    45   1.14677  0.2899
## IQ              1    45   1.92245  0.1724
```

```
flm_FC(mean_networks_FC, "between_FC","Age")
```

```
## [[1]]
##     socialP         age    mentalNM      gender     mean_FD          IQ
##   62.957537    1.392987    1.000000    1.055093    1.104513    1.055296
## socialP:age
##   63.213264
##
## [[2]]
##                       Beta.CI P.value
## (Intercept)   1.191(0.49,1.89)   0.001
## socialP     -0.316(-0.67,0.03)   0.080
## age            -0.037(-0.08,0)   0.072
## mentalNM    -0.007(-0.05,0.04)   0.745
## gender      -0.079(-0.17,0.01)   0.100
## mean_FD      0.063(-0.55,0.67)   0.840
## IQ             -0.003(-0.01,0)   0.104
## socialP:age      0.032(0,0.07)   0.064
##
## [[3]]
##             numDF denDF   F-value p-value
## (Intercept)     1   147 268.44206  <.0001
## social          1   147   0.45982  0.4988
## age             1    45   0.50231  0.4821
## mental          1   147   0.10613  0.7451
## gender          1    45   2.86516  0.0974
## mean_FD         1    45   0.02380  0.8781
## IQ              1    45   2.75792  0.1037
## social:age      1   147   3.48061  0.0641
##
## [[4]]
##             numDF denDF   F-value p-value
## (Intercept)     1    49 220.23113  <.0001
## age             1    45   0.04336  0.8360
```

```
## mental           1    49   0.01936  0.8899
## gender           1    45   3.61112  0.0638
## mean_FD          1    45   0.63007  0.4315
## IQ               1    45   0.92395  0.3416
##
## [[5]]
##             numDF denDF   F-value p-value
## (Intercept)     1    49 204.71504  <.0001
## age             1    45   2.17163  0.1475
## mental          1    49   0.10628  0.7458
## gender          1    45   1.23005  0.2733
## mean_FD         1    45   0.27331  0.6037
## IQ              1    45   3.98449  0.0520
```

```
flm_FC(mean_control_FC, "motor_FC","Age")
```

```
## [[1]]
##     socialP         age    mentalNM      gender     mean_FD          IQ
##   62.957537    1.471361    1.000000    1.055093    1.104513    1.055296
## socialP:age
##   63.291638
##
## [[2]]
##                        Beta.CI P.value
## (Intercept)   1.271(0.48,2.06)   0.002
## socialP     -0.274(-0.73,0.18)   0.236
## age         -0.025(-0.07,0.02)   0.280
## mentalNM     -0.038(-0.1,0.02)   0.190
## gender       0.021(-0.08,0.12)   0.689
## mean_FD      0.128(-0.56,0.81)   0.717
## IQ             -0.005(-0.01,0)   0.018
## socialP:age  0.023(-0.02,0.07)   0.306
##
## [[3]]
##             numDF denDF   F-value p-value
## (Intercept)     1   147 315.86469  <.0001
## social          1   147   1.86183  0.1745
## age             1    45   0.09421  0.7603
## mental          1   147   1.73261  0.1901
## gender          1    45   0.18589  0.6684
## mean_FD         1    45   0.08567  0.7711
## IQ              1    45   5.99097  0.0183
## social:age      1   147   1.05393  0.3063
##
## [[4]]
##             numDF denDF   F-value p-value
## (Intercept)     1    49 178.12368  <.0001
## age             1    45   0.05067  0.8229
## mental          1    49   1.77390  0.1891
## gender          1    45   0.00001  0.9973
## mean_FD         1    45   0.86770  0.3566
## IQ              1    45   3.38008  0.0726
##
## [[5]]
```

```
##              numDF denDF  F-value p-value
## (Intercept)     1    49 318.7121  <.0001
## age             1    45   0.7499  0.3911
## mental          1    49   0.2816  0.5980
## gender          1    45   0.6948  0.4089
## mean_FD         1    45   0.3330  0.5668
## IQ              1    45   6.0423  0.0179
```

```
flm_FC(mean_control_FC, "mirror_FC","Age")
```

```
## [[1]]
##     socialP         age    mentalNM      gender     mean_FD          IQ
##   62.957537    1.376867    1.000000    1.055093    1.104513    1.055296
## socialP:age
##   63.197144
##
## [[2]]
##                          Beta.CI P.value
## (Intercept)   1.256(0.56,1.96)   0.001
## socialP     -0.311(-0.65,0.03)   0.077
## age         -0.008(-0.05,0.03)   0.676
## mentalNM    -0.032(-0.08,0.01)   0.148
## gender      -0.069(-0.16,0.02)   0.150
## mean_FD     -0.007(-0.62,0.61)   0.983
## IQ             -0.004(-0.01,0)   0.026
## socialP:age      0.028(0,0.06)   0.093
##
## [[3]]
##              numDF denDF  F-value p-value
## (Intercept)     1   147 615.9224  <.0001
## social          1   147   0.6907  0.4073
## age             1    45   1.0667  0.3072
## mental          1   147   2.1177  0.1477
## gender          1    45   1.9631  0.1680
## mean_FD         1    45   0.0082  0.9285
## IQ              1    45   5.2863  0.0262
## social:age      1   147   2.8604  0.0929
##
## [[4]]
##              numDF denDF  F-value p-value
## (Intercept)     1    49 435.1631  <.0001
## age             1    45   2.5283  0.1188
## mental          1    49   3.8160  0.0565
## gender          1    45   1.9762  0.1667
## mean_FD         1    45   0.8668  0.3568
## IQ              1    45   1.2614  0.2673
##
## [[5]]
##              numDF denDF  F-value p-value
## (Intercept)     1    49 588.8828  <.0001
## age             1    45   0.0389  0.8446
## mental          1    49   0.0278  0.8683
## gender          1    45   1.2394  0.2715
## mean_FD         1    45   1.4929  0.2281
```

```
## IQ              1    45   9.9820  0.0028
```

```r
flm_FC(mean_control_FC, "salience_FC","Age")
```

```
## [[1]]
##     socialP         age    mentalNM      gender     mean_FD          IQ
##   62.957537    1.365470    1.000000    1.055093    1.104513    1.055296
## socialP:age
##   63.185747
##
## [[2]]
##                         Beta.CI P.value
## (Intercept)   0.269(-0.68,1.22)   0.580
## socialP     -0.537(-0.99,-0.08)   0.022
## age           0.025(-0.03,0.08)   0.352
## mentalNM       0.039(-0.02,0.1)   0.186
## gender         0.022(-0.1,0.15)   0.736
## mean_FD       0.482(-0.35,1.32)   0.263
## IQ                       0(0,0)   0.991
## socialP:age     0.054(0.01,0.1)   0.017
##
## [[3]]
##             numDF denDF  F-value p-value
## (Intercept)     1   147 523.2881  <.0001
## social          1   147   0.4394  0.5084
## age             1    45   3.7533  0.0590
## mental          1   147   1.7623  0.1864
## gender          1    45   0.0135  0.9079
## mean_FD         1    45   1.2841  0.2631
## IQ              1    45   0.0001  0.9914
## social:age      1   147   5.8697  0.0166
##
## [[4]]
##             numDF denDF  F-value p-value
## (Intercept)     1    49 319.0290  <.0001
## age             1    45   5.6806  0.0214
## mental          1    49   0.2278  0.6353
## gender          1    45   0.0421  0.8384
## mean_FD         1    45   0.1720  0.6803
## IQ              1    45   0.1381  0.7119
##
## [[5]]
##             numDF denDF  F-value p-value
## (Intercept)     1    49 631.5690  <.0001
## age             1    45   0.7550  0.3895
## mental          1    49   2.0088  0.1627
## gender          1    45   0.3093  0.5809
## mean_FD         1    45   3.7050  0.0606
## IQ              1    45   0.3157  0.5770
```

```r
# correlation with age
mean_FC <- "mental_FC"
cor.test(mean_networks_FC[mean_networks_FC$social == "P", mean_FC],
     mean_networks_FC[mean_networks_FC$social == "P", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC[mean_networks_FC$social == "P", mean_FC] and mean_networks_FC[mean_networks_F
## t = 1.5069, df = 98, p-value = 0.1351
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.0473314  0.3369444
## sample estimates:
##       cor
## 0.1504857
```

```
cor.test(mean_networks_FC[mean_networks_FC$social == "C", mean_FC],
     mean_networks_FC[mean_networks_FC$social == "C", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC[mean_networks_FC$social == "C", mean_FC] and mean_networks_FC[mean_networks_F
## t = -1.6531, df = 98, p-value = 0.1015
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.34981164  0.03276754
## sample estimates:
##        cor
## -0.1647107
```

```
mean_FC <- "reward_FC"
cor.test(mean_networks_FC[mean_networks_FC$social == "P", mean_FC],
     mean_networks_FC[mean_networks_FC$social == "P", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC[mean_networks_FC$social == "P", mean_FC] and mean_networks_FC[mean_networks_F
## t = 0.73604, df = 98, p-value = 0.4635
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1240786  0.2666808
## sample estimates:
##        cor
## 0.07414653
```

```
cor.test(mean_networks_FC[mean_networks_FC$social == "C", mean_FC],
     mean_networks_FC[mean_networks_FC$social == "C", "age"])
```

```
##
##  Pearson's product-moment correlation
##
```

```
## data:  mean_networks_FC[mean_networks_FC$social == "C", mean_FC] and mean_networks_FC[mean_networks_I
## t = -2.114, df = 98, p-value = 0.03705
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.38929113 -0.01295517
## sample estimates:
##        cor
## -0.2088419
```

```
mean_FC <- "between_FC"
cor.test(mean_networks_FC[mean_networks_FC$social == "P", mean_FC],
     mean_networks_FC[mean_networks_FC$social == "P", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC[mean_networks_FC$social == "P", mean_FC] and mean_networks_FC[mean_networks_I
## t = 0.24697, df = 98, p-value = 0.8054
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1723224  0.2202789
## sample estimates:
##        cor
## 0.02493985
```

```
cor.test(mean_networks_FC[mean_networks_FC$social == "C", mean_FC],
     mean_networks_FC[mean_networks_FC$social == "C", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC[mean_networks_FC$social == "C", mean_FC] and mean_networks_FC[mean_networks_I
## t = -1.7433, df = 98, p-value = 0.08441
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.35766798  0.02379467
## sample estimates:
##       cor
## -0.173434
```

```
mean_FC <-  "salience_FC"
cor.test(mean_control_FC[mean_control_FC$social == "P", mean_FC],
     mean_control_FC[mean_control_FC$social == "P", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_control_FC[mean_control_FC$social == "P", mean_FC] and mean_control_FC[mean_control_FC$so
## t = 3.1021, df = 98, p-value = 0.00251
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.1090068 0.4679560
```

```
## sample estimates:
##       cor
## 0.2990225
```

```r
cor.test(mean_control_FC[mean_control_FC$social == "C", mean_FC],
     mean_control_FC[mean_control_FC$social == "C", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_control_FC[mean_control_FC$social == "C", mean_FC] and mean_control_FC[mean_control_FC$so
## t = 0.97311, df = 98, p-value = 0.3329
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1005225  0.2886979
## sample estimates:
##        cor
## 0.09782716
```

```r
mean_FC <-  "mirror_FC"
cor.test(mean_control_FC[mean_control_FC$social == "P", mean_FC],
     mean_control_FC[mean_control_FC$social == "P", "age"])
```

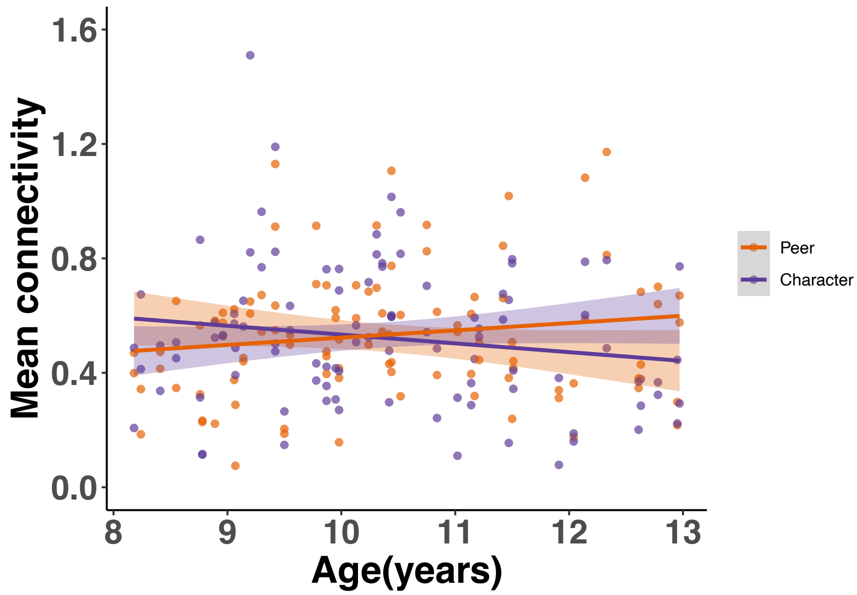
```
##
##  Pearson's product-moment correlation
##
## data:  mean_control_FC[mean_control_FC$social == "P", mean_FC] and mean_control_FC[mean_control_FC$so
## t = 1.9304, df = 98, p-value = 0.05645
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.005220282  0.373761293
## sample estimates:
##       cor
## 0.1913941
```

```r
cor.test(mean_control_FC[mean_control_FC$social == "C", mean_FC],
     mean_control_FC[mean_control_FC$social == "C", "age"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_control_FC[mean_control_FC$social == "C", mean_FC] and mean_control_FC[mean_control_FC$so
## t = 0.22014, df = 98, p-value = 0.8262
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1749499  0.2176996
## sample estimates:
##        cor
## 0.02223217
```

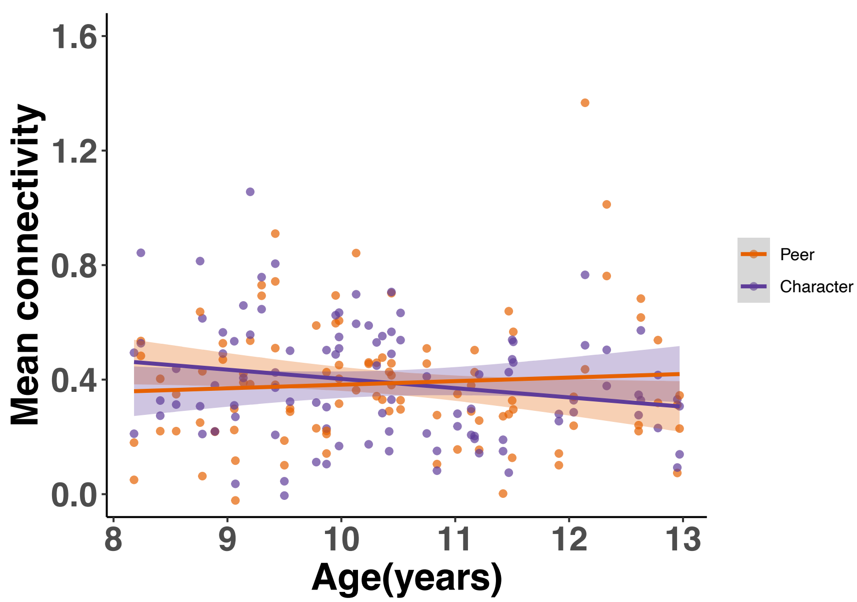
```r
# scatterplots for interaction effects of social interaction and age
FC_scatterplot(mean_networks_FC,"age","mental_FC","Age(years)","Age")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



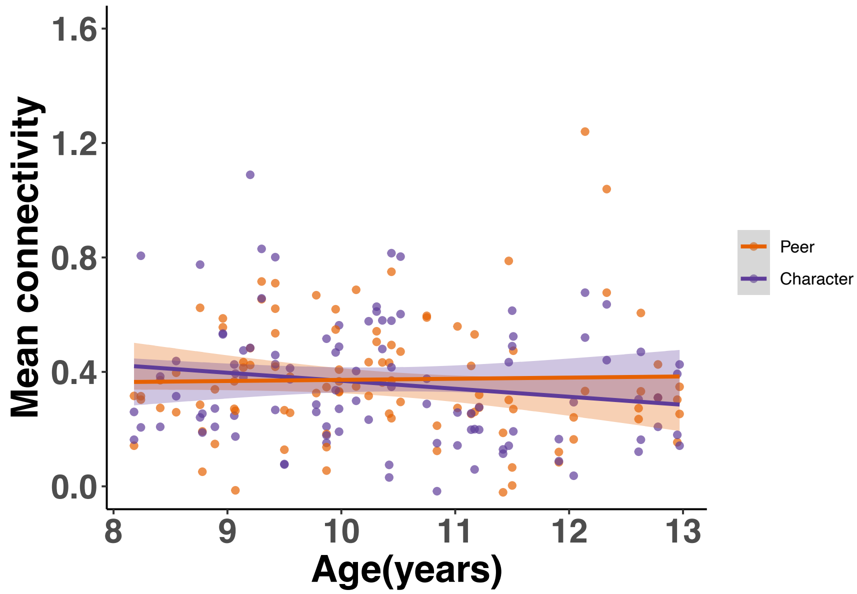

```r
FC_scatterplot(mean_networks_FC,"age","reward_FC","Age(years)","Age")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



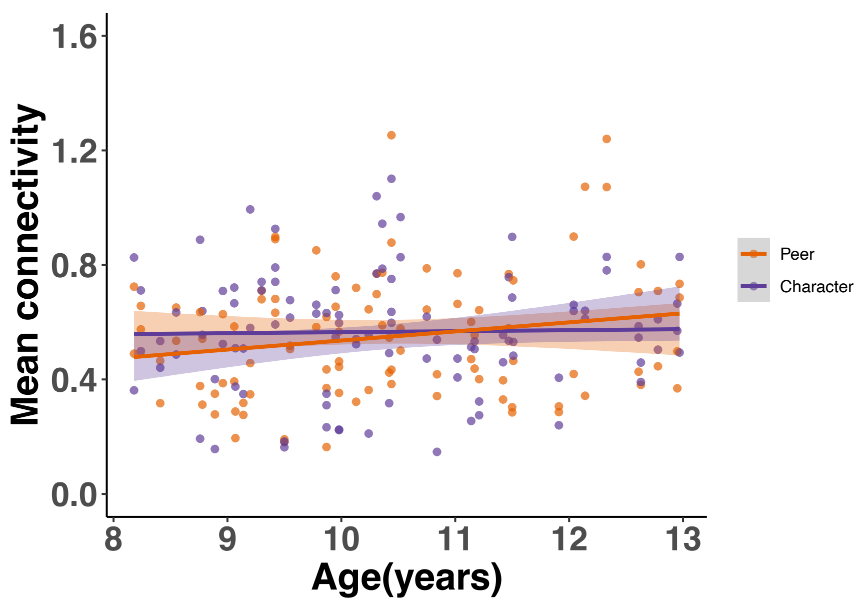

```r
FC_scatterplot(mean_networks_FC,"age","between_FC","Age(years)","Age")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



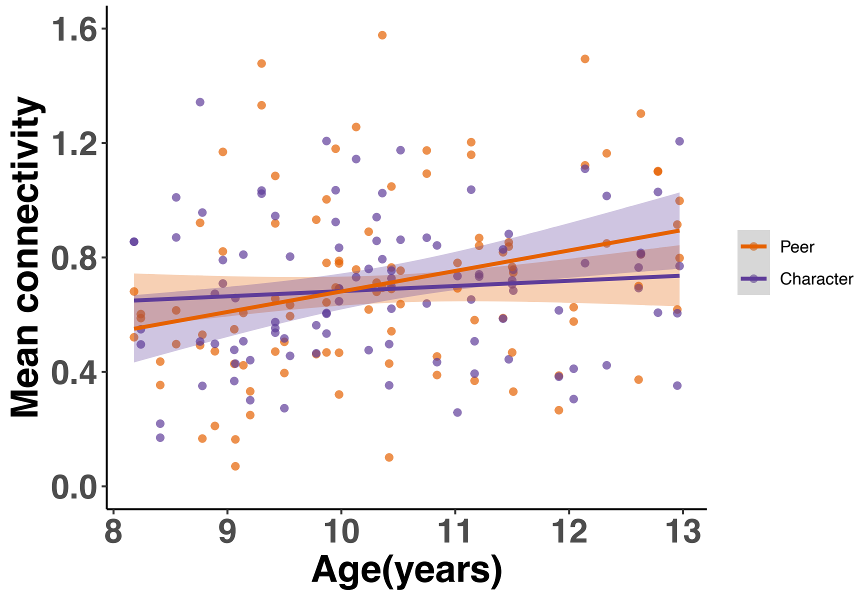

```
FC_scatterplot(mean_control_FC,"age","mirror_FC","Age(years)","Age")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



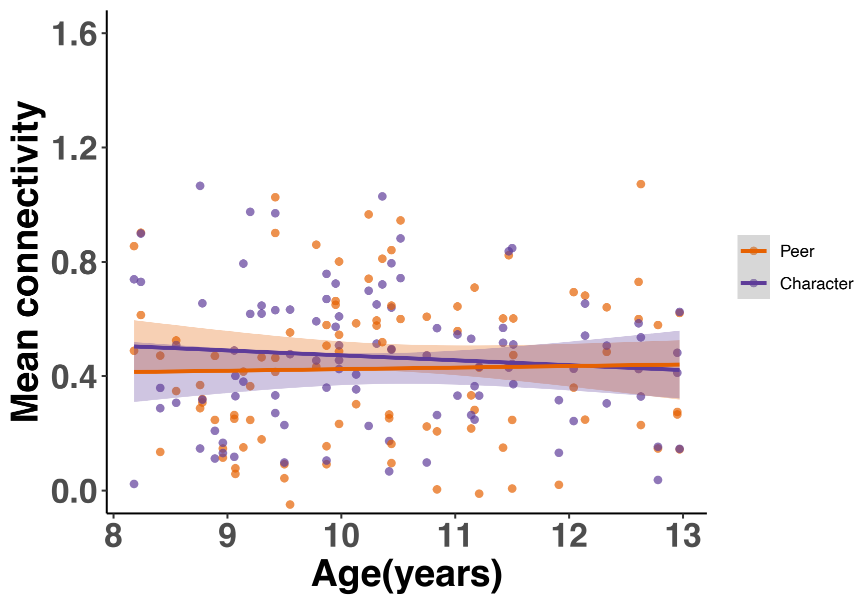

```
FC_scatterplot(mean_control_FC,"age","salience_FC","Age(years)","Age")
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```
FC_scatterplot(mean_control_FC,"age","motor_FC","Age(years)","Age")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



FC differences between subjects at upper vs. lower quantile of age

```
# connectivity averaged across collapsed conditions
tmp <- as.data.frame(matrix(0,100,0))
tmp$subj <- rep(mean_networks_FC$Subject[!duplicated(mean_networks_FC$Subject)],2)
tmp$age <- rep(mean_networks_FC$age[!duplicated(mean_networks_FC$Subject)],2)
tmp$social <- rep(c("P","C"),each = 50)
```

```r
tmp$mental_FC <- c((mean_networks_FC$mental_FC[mean_networks_FC$conditions == "PM"] +
                mean_networks_FC$mental_FC[mean_networks_FC$conditions == "PNM"])/2,
         (mean_networks_FC$mental_FC[mean_networks_FC$conditions == "CM"] +
            mean_networks_FC$mental_FC[mean_networks_FC$conditions == "CNM"])/2)

tmp$reward_FC <- c((mean_networks_FC$reward_FC[mean_networks_FC$conditions == "PM"] +
                mean_networks_FC$reward_FC[mean_networks_FC$conditions == "PNM"])/2,
           (mean_networks_FC$reward_FC[mean_networks_FC$conditions == "CM"] +
                mean_networks_FC$reward_FC[mean_networks_FC$conditions == "CNM"])/2)

tmp$between_FC <- c((mean_networks_FC$between_FC[mean_networks_FC$conditions == "PM"] +
                mean_networks_FC$between_FC[mean_networks_FC$conditions == "PNM"])/2,
           (mean_networks_FC$between_FC[mean_networks_FC$conditions == "CM"] +
                mean_networks_FC$between_FC[mean_networks_FC$conditions == "CNM"])/2)

# FC differences: upper vs. lower quantile of age
age <- summary(variables_all$age[!duplicated(variables_all$Subject)])
print(paste0("The upper quartile of age is ", round(age["3rd Qu."],2)))
```

```
## [1] "The upper quartile of age is 11.37"
```

```r
print(paste0("The lower quartile of age is ", age["1st Qu."]))
```

```
## [1] "The lower quartile of age is 9.33"
```

```r
networks <- c("mental_FC","reward_FC","between_FC")

contrast_FC_age <- as.data.frame(matrix(0,3,3))
colnames(contrast_FC_age)  <- c("network","older children","younger children")

k <-0
for (net in networks) {
    k <- k+1
    tt1 <- t.test(tmp[tmp$age > as.numeric(age["3rd Qu."]) & tmp$social == "P", net],
              tmp[tmp$age > as.numeric(age["3rd Qu."]) & tmp$social == "C",net],
              paired = T)

    tt2 <- t.test(tmp[tmp$age < as.numeric(age["1st Qu."]) & tmp$social == "P",net],
              tmp[tmp$age < as.numeric(age["1st Qu."]) & tmp$social == "C",net],
              paired = T)

    contrast_FC_age[k, 1] <- net
    contrast_FC_age[k, 2:3] <- c(paste0("t=", round(tt1$statistic,3),", p=",round(tt1$p.value,3)),
                     paste0("t=", round(tt2$statistic,3),", p=",round(tt2$p.value,3)))

}

    knitr::kable(contrast_FC_age)
```

network	older children	younger children
mental_FC	t=1.928, p=0.078	t=-2.331, p=0.038
reward_FC	t=0.928, p=0.372	t=-4.552, p=0.001
between_FC	t=0.677, p=0.511	t=-2.299, p=0.04

ROI analysis

```
# load data
mental_node_FC <- read.table(here("data/mental_nodes_FC.txt"), header = T)
reward_node_FC <- read.table(here("data/reward_nodes_FC.txt"), header = T)
between_node_FC <- read.table(here("data/between_nodes_FC.txt"), header = T)
salience_node_FC <- read.table(here("data/salience_nodes_FC.txt"), header = T)
mirror_node_FC <- read.table(here("data/mirror_nodes_FC.txt"), header = T)
motor_node_FC <- read.table(here("data/motor_nodes_FC.txt"), header = T)

# mental network
ROIs <- c("dmPFC","vmPFC","PCC","RTPJ","LTPJ","RATL","LATL")
colnames(mental_node_FC)
```

```
##  [1] "Subject"    "conditions" "social"     "mental"     "age"
##  [6] "gender"     "mean_FD"    "IQ"         "RT"         "Accuracy"
## [11] "dmPFC"      "vmPFC"      "PCC"        "RTPJ"       "LTPJ"
## [16] "RATL"       "LATL"
```

```
flm_sum1 <- as.data.frame(matrix(0, 7, 2))
rownames(flm_sum1) <- ROIs
colnames(flm_sum1) <- c("F-value", "p-value")

k <- 0
for (ROI in ROIs) {
    k <- k + 1
    flm_ROI <- flm_FC(mental_node_FC, ROI,"Age")

    flm_sum1[k, ] <- c(flm_ROI[[3]]$`F-value`[4], flm_ROI[[3]]$`p-value`[4])
}

# reward network
ROIs <- c("LOFC","RVFC","ACC","LVS","RVS","LAmygdala","RAmygdala" )
colnames(reward_node_FC)
```

```
##  [1] "Subject"    "conditions" "social"     "mental"     "age"
##  [6] "gender"     "mean_FD"    "IQ"         "RT"         "Accuracy"
## [11] "LOFC"       "RVFC"       "ACC"        "LVS"        "RVS"
## [16] "LAmygdala"  "RAmygdala"
```

```
flm_sum2 <- as.data.frame(matrix(0, 7, 2))
rownames(flm_sum2) <- ROIs
colnames(flm_sum2) <- c("F-value", "p-value")
```

```r
k <- 0
for (ROI in ROIs) {
    k <- k + 1
    flm_ROI <- flm_FC(reward_node_FC, ROI,"Age")

    flm_sum2[k, ] <- c(flm_ROI[[3]]$`F-value`[4], flm_ROI[[3]]$`p-value`[4])

}

# between noodes:
ROIs <- c("dmPFC","vmPFC","PCC","RTPJ","LTPJ","RATL","LATL","LOFC","RVFC","ACC","LVS","RVS","LAmygdala"

flm_sum3 <- as.data.frame(matrix(0, 14, 2))
rownames(flm_sum3) <- ROIs
colnames(flm_sum3) <- c("F-value", "p-value")

k <- 0
for (ROI in ROIs) {
    k <- k + 1
    flm_ROI <- flm_FC(between_node_FC, ROI,"Age")

    flm_sum3[k, ] <- c(flm_ROI[[3]]$`F-value`[8], flm_ROI[[3]]$`p-value`[8])

}

# significant interaction effects
knitr::kable(rbind.data.frame(flm_sum1[flm_sum1$`p-value` < 0.05,],
                  flm_sum2[flm_sum2$`p-value` < 0.05,],
                  flm_sum3[flm_sum3$`p-value` < 0.05,]))
```

	F-value	p-value
dmPFC	4.907437	0.0282794
ACC	7.999469	0.0053325
dmPFC1	5.798029	0.0172835
LTPJ	5.173727	0.0243779
LATL	5.499957	0.0203539
ACC1	5.817598	0.0170996
LVS	4.788573	0.0302281

```r
p.adjust(c(flm_sum1$`p-value`,flm_sum2$`p-value`,flm_sum3$`p-value`))
```

```
##  [1] 0.6504256 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000
##  [8] 1.0000000 1.0000000 0.1493110 1.0000000 1.0000000 1.0000000 1.0000000
## [15] 0.4616898 1.0000000 1.0000000 1.0000000 0.5850687 1.0000000 0.5088469
## [22] 1.0000000 1.0000000 0.4616898 0.6650178 1.0000000 1.0000000 1.0000000
```

```r
## regions within specificity and control networks
# motor nodes
colnames(motor_node_FC)[1] <- "Subject"

ROIs <- c("X3","X4","X5")
```

```r
flm_sum <- as.data.frame(matrix(0, 3, 2))
rownames(flm_sum) <- ROIs
colnames(flm_sum) <- c("F-value", "p-value")

k <- 0
for (ROI in ROIs) {
    k <- k + 1
    flm_ROI <- flm_FC(motor_node_FC, ROI,"Age")
    flm_sum[k, ] <- c(flm_ROI[[3]]$`F-value`[8], flm_ROI[[3]]$`p-value`[8])

}

flm_sum[flm_sum$`p-value` < 0.05,]
```

```
## [1] F-value p-value
## <0 rows> (or 0-length row.names)
```

```r
# mirror nodes
colnames(mirror_node_FC)[1] <- "Subject"

ROIs <- c("X3","X4","X5","X6","X7","X8","X9","X10","X11","X12")
flm_sum <- as.data.frame(matrix(0, 10, 2))
rownames(flm_sum) <- ROIs
colnames(flm_sum) <- c("F-value", "p-value")

k <- 0
for (ROI in ROIs) {
    k <- k + 1
    flm_ROI <- flm_FC(mirror_node_FC, ROI,"Age")

    flm_sum[k, ] <- c(flm_ROI[[3]]$`F-value`[8], flm_ROI[[3]]$`p-value`[8])

}

flm_sum[flm_sum$`p-value` < 0.05,]
```

```
## [1] F-value p-value
## <0 rows> (or 0-length row.names)
```

```r
# salience nodes
colnames(salience_node_FC)[1] <- "Subject"

ROIs <- c("RdACC", "LaInsula", "RaInsula")
flm_sum <- as.data.frame(matrix(0, 3, 2))
rownames(flm_sum) <- ROIs
colnames(flm_sum) <- c("F-value", "p-value")

k <- 0
for (ROI in ROIs) {
    k <- k + 1
    flm_ROI <- flm_FC(salience_node_FC, ROI,"Age")
```

```
    flm_sum[k, ] <- c(flm_ROI[[3]]$`F-value`[8], flm_ROI[[3]]$`p-value`[8])

}

flm_sum[flm_sum$`p-value` < 0.05,]
```

```
## [1] F-value p-value
## <0 rows> (or 0-length row.names)
```

Correlations between salience/mirror neuron and mentalizing/reward networks

```
tmp0$mirror <- (mean_control_FC$mirror_FC[mean_control_FC$conditions == "PM"] +
            mean_control_FC$mirror_FC[mean_control_FC$conditions == "PNM"] +
            mean_control_FC$mirror_FC[mean_control_FC$conditions == "CM"] +
            mean_control_FC$mirror_FC[mean_control_FC$conditions == "CNM"])/4

tmp0$salience <- (mean_control_FC$salience_FC[mean_control_FC$conditions == "PM"] +
         mean_control_FC$salience_FC[mean_control_FC$conditions == "PNM"] +
         mean_control_FC$salience_FC[mean_control_FC$conditions == "CM"] +
         mean_control_FC$salience_FC[mean_control_FC$conditions == "CNM"])/4

# correlations between salience network and mentalizing/reward networks
cor.test(tmp0$mentalizing,tmp0$salience)
```

```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$mentalizing and tmp0$salience
## t = 3.724, df = 48, p-value = 0.0005155
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.2247139 0.6642578
## sample estimates:
##       cor
## 0.4734481
```

```
cor.test(tmp0$reward,tmp0$salience)
```

```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$reward and tmp0$salience
## t = 4.3194, df = 48, p-value = 7.815e-05
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.2940001 0.7037641
## sample estimates:
##       cor
## 0.5290532
```

```r
# correlation between mirror neuron network and mentalizing network
cor.test(tmp0$mentalizing,tmp0$mirror)
```

```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$mentalizing and tmp0$mirror
## t = 6.0831, df = 48, p-value = 1.872e-07
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.4672542 0.7925798
## sample estimates:
##       cor
## 0.6597902
```

```r
cor.test(mean_networks_FC$mental_FC[mean_networks_FC$social == "P"],
     mean_control_FC$mirror_FC[mean_control_FC$social == "P"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC$mental_FC[mean_networks_FC$social == "P"] and mean_control_FC$mirror_FC[mean_
## t = 9.1785, df = 98, p-value = 7.343e-15
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.5579963 0.7730756
## sample estimates:
##       cor
## 0.6798972
```

```r
cor.test(mean_networks_FC$mental_FC[mean_networks_FC$social == "C"],
     mean_control_FC$mirror_FC[mean_control_FC$social == "C"])
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_networks_FC$mental_FC[mean_networks_FC$social == "C"] and mean_control_FC$mirror_FC[mean_
## t = 8.3404, df = 98, p-value = 4.739e-13
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.5127933 0.7462865
## sample estimates:
##       cor
## 0.6443148
```

Brain-behavior correlations

```r
# regression analysis
flm_FC(mean_networks_FC, "mental_FC","RT")
```

```
## [[1]]
##    socialP         RT   mentalNM     gender    mean_FD         IQ socialP:RT
##  44.073121   1.411943   1.000758   1.029413   1.072457   1.009231  42.605589
##
## [[2]]
##                        Beta.CI P.value
## (Intercept)    0.493(-0.12,1.1)   0.115
## socialP         0.586(0.28,0.9)   0.000
## RT            0.096(-0.07,0.26)   0.245
## mentalNM     -0.041(-0.09,0.01)   0.084
## gender       -0.051(-0.16,0.06)   0.352
## mean_FD      -0.127(-0.83,0.58)   0.724
## IQ                       0(0,0)   0.834
## socialP:RT  -0.283(-0.43,-0.13)   0.000
##
## [[3]]
##             numDF denDF  F-value p-value
## (Intercept)     1   146 406.9052  <.0001
## social          1   146   0.2058  0.6508
## RT              1   146   0.5195  0.4722
## mental          1   146   3.0169  0.0845
## gender          1    46   0.8784  0.3535
## mean_FD         1    46   0.1352  0.7148
## IQ              1    46   0.0097  0.9218
## social:RT       1   146  13.7188  0.0003
##
## [[4]]
##             numDF denDF  F-value p-value
## (Intercept)     1    48 372.7158  <.0001
## RT              1    48   4.4742  0.0396
## mental          1    48   3.7505  0.0587
## gender          1    46   1.7138  0.1970
## mean_FD         1    46   0.0015  0.9690
## IQ              1    46   0.0734  0.7876
##
## [[5]]
##             numDF denDF   F-value p-value
## (Intercept)     1    48 274.23366  <.0001
## RT              1    48   2.12712  0.1512
## mental          1    48   0.69633  0.4082
## gender          1    46   0.08313  0.7744
## mean_FD         1    46   0.51989  0.4745
## IQ              1    46   0.35477  0.5543
```

```
flm_FC(mean_networks_FC, "reward_FC","RT")
```

```
## [[1]]
##    socialP         RT   mentalNM     gender    mean_FD         IQ socialP:RT
##  44.052871   1.422604   1.000728   1.029437   1.073169   1.009299  42.601047
##
## [[2]]
##                        Beta.CI P.value
## (Intercept)   0.518(-0.03,1.07)   0.067
## socialP        0.396(0.11,0.68)   0.008
```

```
## RT              0.096(-0.05,0.24)   0.205
## mentalNM       -0.019(-0.06,0.02)   0.394
## gender         -0.043(-0.14,0.05)   0.383
## mean_FD         0.022(-0.61,0.66)   0.945
## IQ                -0.002(-0.01,0)   0.233
## socialP:RT  -0.195(-0.33,-0.06)   0.007
##
## [[3]]
##             numDF denDF   F-value p-value
## (Intercept)     1   146 271.99155  <.0001
## social          1   146   0.02033  0.8868
## RT              1   146   0.00006  0.9939
## mental          1   146   0.73277  0.3934
## gender          1    46   0.84950  0.3615
## mean_FD         1    46   0.00113  0.9733
## IQ              1    46   1.26065  0.2674
## social:RT       1   146   7.55083  0.0068
##
## [[4]]
##             numDF denDF   F-value p-value
## (Intercept)     1    48 201.62591  <.0001
## RT              1    48   1.61474  0.2100
## mental          1    48   0.28363  0.5968
## gender          1    46   1.65415  0.2048
## mean_FD         1    46   0.47240  0.4953
## IQ              1    46   1.63198  0.2078
##
## [[5]]
##             numDF denDF   F-value p-value
## (Intercept)     1    48 258.14037  <.0001
## RT              1    48   2.64605  0.1104
## mental          1    48   0.43645  0.5120
## gender          1    46   0.06701  0.7969
## mean_FD         1    46   0.78285  0.3809
## IQ              1    46   0.92704  0.3407
```

```
flm_FC(mean_networks_FC, "between_FC","RT")
```

```
## [[1]]
##    socialP         RT   mentalNM     gender    mean_FD         IQ socialP:RT
##  44.015188   1.443062   1.000676   1.029480   1.074370   1.009424  42.592478
##
## [[2]]
##                          Beta.CI P.value
## (Intercept)   0.513(-0.02,1.04)   0.060
## socialP        0.437(0.15,0.73)   0.004
## RT              0.111(-0.03,0.26)   0.136
## mentalNM       -0.007(-0.05,0.04)   0.739
## gender         -0.068(-0.16,0.02)   0.149
## mean_FD         0.148(-0.46,0.75)   0.635
## IQ                -0.003(-0.01,0)   0.133
## socialP:RT  -0.206(-0.35,-0.07)   0.005
##
## [[3]]
```

```
##              numDF denDF   F-value p-value
## (Intercept)     1   146 264.97942  <.0001
## social          1   146   0.47240  0.4930
## RT              1   146   0.08010  0.7776
## mental          1   146   0.11392  0.7362
## gender          1    46   2.49524  0.1210
## mean_FD         1    46   0.12125  0.7293
## IQ              1    46   2.06558  0.1574
## social:RT       1   146   8.31904  0.0045
##
## [[4]]
##              numDF denDF   F-value p-value
## (Intercept)     1    48 223.57397  <.0001
## RT              1    48   0.86054  0.3582
## mental          1    48   0.01455  0.9045
## gender          1    46   3.86654  0.0553
## mean_FD         1    46   0.99122  0.3247
## IQ              1    46   1.21283  0.2765
##
## [[5]]
##              numDF denDF   F-value p-value
## (Intercept)     1    48 203.17806  <.0001
## RT              1    48   4.30709  0.0433
## mental          1    48   0.14034  0.7096
## gender          1    46   0.56957  0.4543
## mean_FD         1    46   0.26116  0.6118
## IQ              1    46   2.80491  0.1008
```

```
flm_FC(mean_control_FC, "motor_FC","RT")
```

```
## [[1]]
##    socialP         RT   mentalNM     gender    mean_FD         IQ socialP:RT
##  43.888245   1.516555   1.000543   1.029606   1.077491   1.009844  42.562748
##
## [[2]]
##                       Beta.CI P.value
## (Intercept)   0.788(0.18,1.39)   0.011
## socialP      0.289(-0.09,0.66)   0.133
## RT           0.086(-0.09,0.26)   0.334
## mentalNM    -0.038(-0.09,0.02)   0.187
## gender       0.028(-0.07,0.13)   0.588
## mean_FD      0.184(-0.49,0.86)   0.596
## IQ             -0.005(-0.01,0)   0.020
## socialP:RT  -0.161(-0.34,0.02)   0.085
##
## [[3]]
##              numDF denDF   F-value p-value
## (Intercept)     1   146 316.13053  <.0001
## social          1   146   1.88006  0.1724
## RT              1   146   0.01370  0.9070
## mental          1   146   1.75755  0.1870
## gender          1    46   0.22331  0.6388
## mean_FD         1    46   0.10355  0.7491
## IQ              1    46   5.54297  0.0229
```

```
## social:RT       1   146   3.01184  0.0848
##
## [[4]]
##             numDF denDF   F-value p-value
## (Intercept)     1    48 183.92511  <.0001
## RT              1    48   0.19188  0.6633
## mental          1    48   1.71962  0.1960
## gender          1    46   0.00210  0.9637
## mean_FD         1    46   0.91786  0.3430
## IQ              1    46   3.94674  0.0529
##
## [[5]]
##             numDF denDF  F-value p-value
## (Intercept)     1    48 318.1340  <.0001
## RT              1    48   0.8001  0.3755
## mental          1    48   0.2968  0.5884
## gender          1    46   1.0191  0.3180
## mean_FD         1    46   0.3327  0.5669
## IQ              1    46   5.0954  0.0288
```

```
flm_FC(mean_control_FC, "mirror_FC","RT")
```

```
## [[1]]
##    socialP         RT   mentalNM     gender    mean_FD         IQ socialP:RT
##  44.027812   1.436124   1.000693   1.029466   1.073985   1.009382  42.595365
##
## [[2]]
##                       Beta.CI P.value
## (Intercept)     1.217(0.7,1.74)   0.000
## socialP         0.36(0.08,0.64)   0.013
## RT            -0.01(-0.15,0.13)   0.893
## mentalNM     -0.031(-0.07,0.01)   0.152
## gender       -0.072(-0.16,0.02)   0.123
## mean_FD       0.065(-0.53,0.66)   0.832
## IQ              -0.004(-0.01,0)   0.013
## socialP:RT  -0.189(-0.32,-0.05)   0.007
##
## [[3]]
##             numDF denDF  F-value p-value
## (Intercept)     1   146 634.6668  <.0001
## social          1   146   0.7183  0.3981
## RT              1   146   2.5448  0.1128
## mental          1   146   2.0831  0.1511
## gender          1    46   2.6410  0.1110
## mean_FD         1    46   0.0002  0.9901
## IQ              1    46   6.2242  0.0163
## social:RT       1   146   7.4875  0.0070
##
## [[4]]
##             numDF denDF  F-value p-value
## (Intercept)     1    48 475.9026  <.0001
## RT              1    48   4.3633  0.0420
## mental          1    48   3.6112  0.0634
## gender          1    46   2.9927  0.0903
```

```
## mean_FD         1    46   0.9909  0.3247
## IQ              1    46   2.9480  0.0927
##
## [[5]]
##             numDF denDF  F-value p-value
## (Intercept)     1    48 583.0405  <.0001
## RT              1    48   0.0464  0.8303
## mental          1    48   0.0293  0.8648
## gender          1    46   1.2263  0.2739
## mean_FD         1    46   1.5469  0.2199
## IQ              1    46   9.2252  0.0039
```

```
flm_FC(mean_control_FC, "salience_FC","RT")
```

```
## [[1]]
##    socialP        RT    mentalNM     gender    mean_FD         IQ socialP:RT
##  44.049624  1.424336   1.000723   1.029441   1.073279   1.009309  42.600314
##
## [[2]]
##                       Beta.CI P.value
## (Intercept)    0.85(0.11,1.59)   0.025
## socialP      0.169(-0.22,0.56)   0.394
## RT          -0.052(-0.25,0.15)   0.606
## mentalNM       0.04(-0.02,0.1)   0.186
## gender      -0.001(-0.13,0.13)   0.987
## mean_FD      0.341(-0.51,1.19)   0.434
## IQ             -0.001(-0.01,0)   0.616
## socialP:RT  -0.077(-0.26,0.11)   0.423
##
## [[3]]
##             numDF denDF  F-value p-value
## (Intercept)     1   146 492.6899  <.0001
## social          1   146   0.4229  0.5165
## RT              1   146   0.7242  0.3962
## mental          1   146   1.7561  0.1872
## gender          1    46   0.0216  0.8839
## mean_FD         1    46   0.5599  0.4581
## IQ              1    46   0.2299  0.6339
## social:RT       1   146   0.6450  0.4232
##
## [[4]]
##             numDF denDF   F-value p-value
## (Intercept)     1    48 291.59839  <.0001
## RT              1    48   0.97694  0.3279
## mental          1    48   0.25242  0.6177
## gender          1    46   0.23582  0.6295
## mean_FD         1    46   0.00001  0.9970
## IQ              1    46   0.04911  0.8256
##
## [[5]]
##             numDF denDF  F-value p-value
## (Intercept)     1    48 618.0971  <.0001
## RT              1    48   0.1809  0.6725
## mental          1    48   2.0318  0.1605
```

```
## gender          1    46   0.1706  0.6815
## mean_FD         1    46   2.9713  0.0915
## IQ              1    46   0.6487  0.4247
```

```r
# correlations between RT and FC averaged across conditions
tmp0$RT <- (mean_networks_FC$RT[mean_networks_FC$conditions=="PM"] +
            mean_networks_FC$RT[mean_networks_FC$conditions=="PNM"] +
            mean_networks_FC$RT[mean_networks_FC$conditions=="CM"] +
            mean_networks_FC$RT[mean_networks_FC$conditions=="CNM"])/4

# correlation between RT within-mentalizing, reward, and between-networks
cor.test(tmp0$mentalizing, tmp0$RT)
```

```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$mentalizing and tmp0$RT
## t = -0.16419, df = 48, p-value = 0.8703
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3000616  0.2563456
## sample estimates:
##         cor
## -0.02369269
```

```r
cor.test(tmp0$reward, tmp0$RT)
```

```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$reward and tmp0$RT
## t = 0.2718, df = 48, p-value = 0.7869
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.2417845  0.3141216
## sample estimates:
##        cor
## 0.03920144
```

```r
cor.test(tmp0$between, tmp0$RT)
```

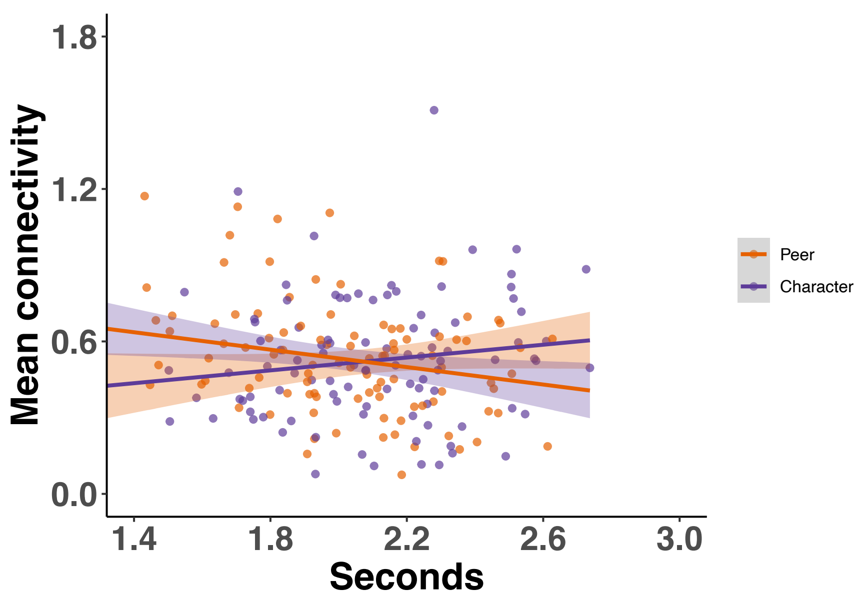
```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$between and tmp0$RT
## t = 0.86768, df = 48, p-value = 0.3899
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1596003  0.3891549
## sample estimates:
##      cor
## 0.124268
```

```r
# correlation between RT and mirror neuron networks
tmp0$mirror <- (mean_control_FC$mirror_FC[mean_control_FC$conditions == "PM"] +
            mean_control_FC$mirror_FC[mean_control_FC$conditions == "PNM"] +
            mean_control_FC$mirror_FC[mean_control_FC$conditions == "CM"] +
            mean_control_FC$mirror_FC[mean_control_FC$conditions == "CNM"])/4

cor.test(tmp0$mirror, tmp0$RT)
```

```
##
##  Pearson's product-moment correlation
##
## data:  tmp0$mirror and tmp0$RT
## t = -0.84355, df = 48, p-value = 0.4031
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.3862183  0.1629665
## sample estimates:
##        cor
## -0.1208638
```

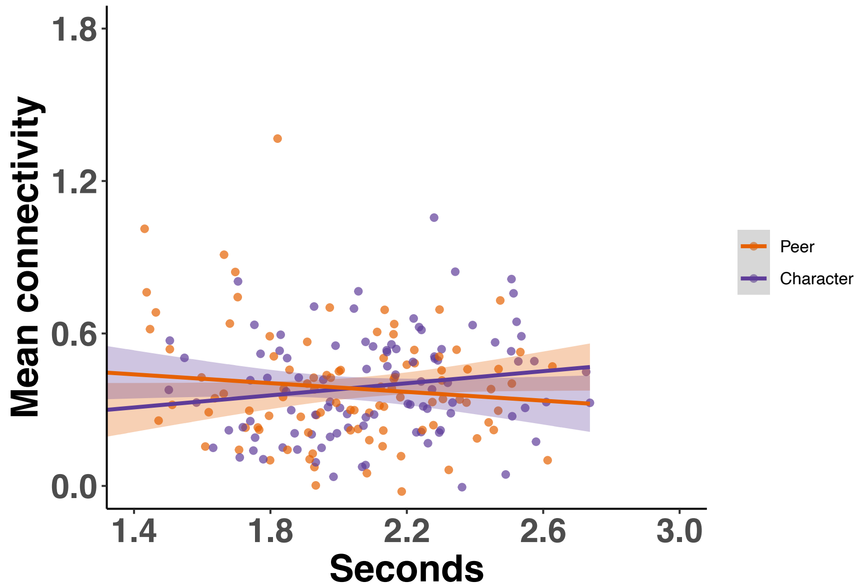
```r
# scatter plot
FC_scatterplot(mean_networks_FC,"RT","mental_FC","Seconds","RT")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



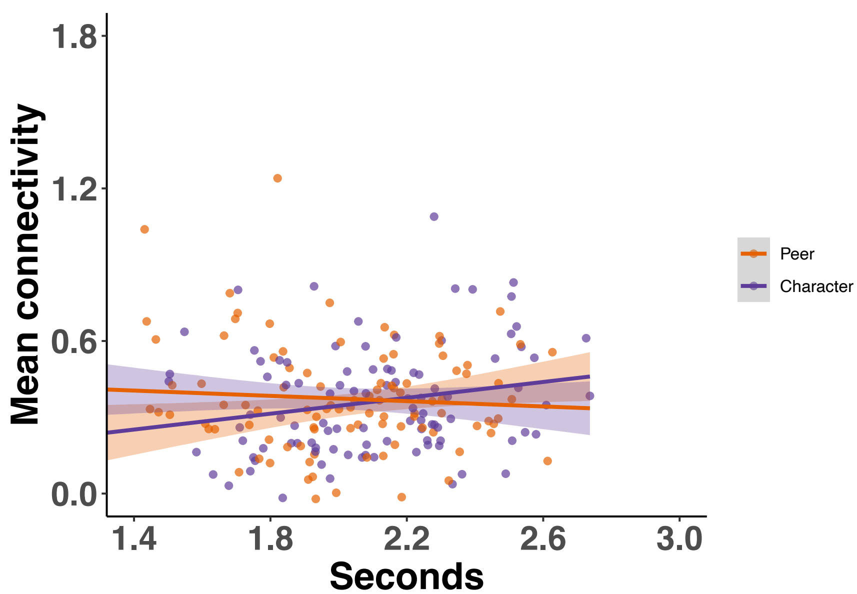

```r
FC_scatterplot(mean_networks_FC,"RT","reward_FC","Seconds","RT")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



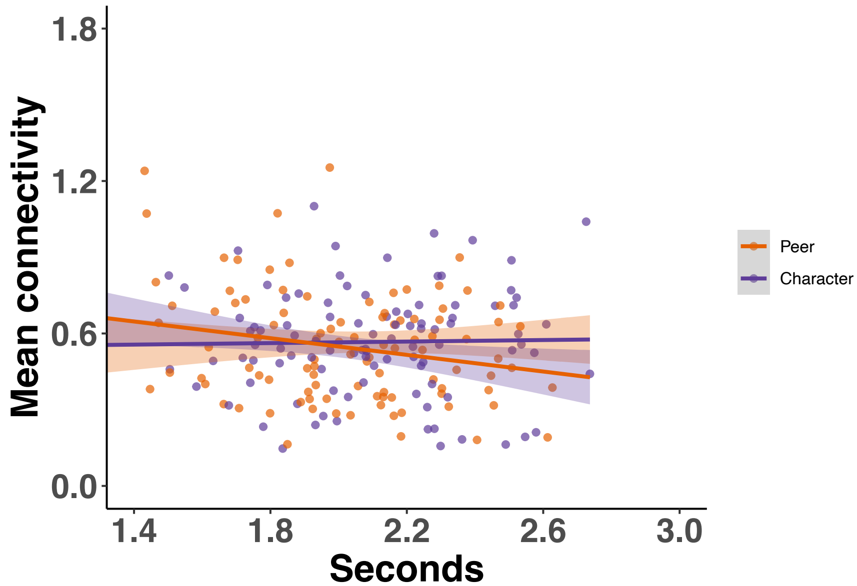

```
FC_scatterplot(mean_networks_FC,"RT","between_FC","Seconds","RT")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



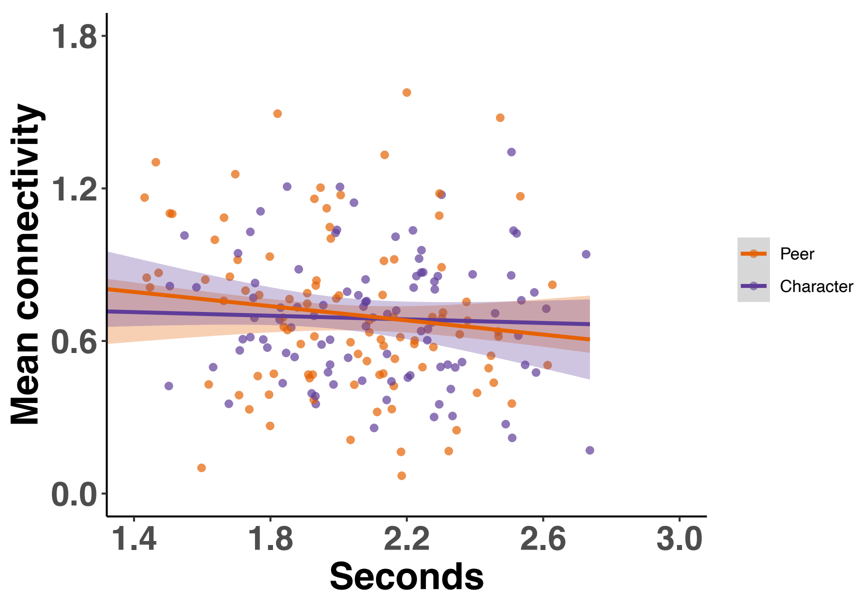

```
FC_scatterplot(mean_control_FC,"RT","mirror_FC","Seconds","RT")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



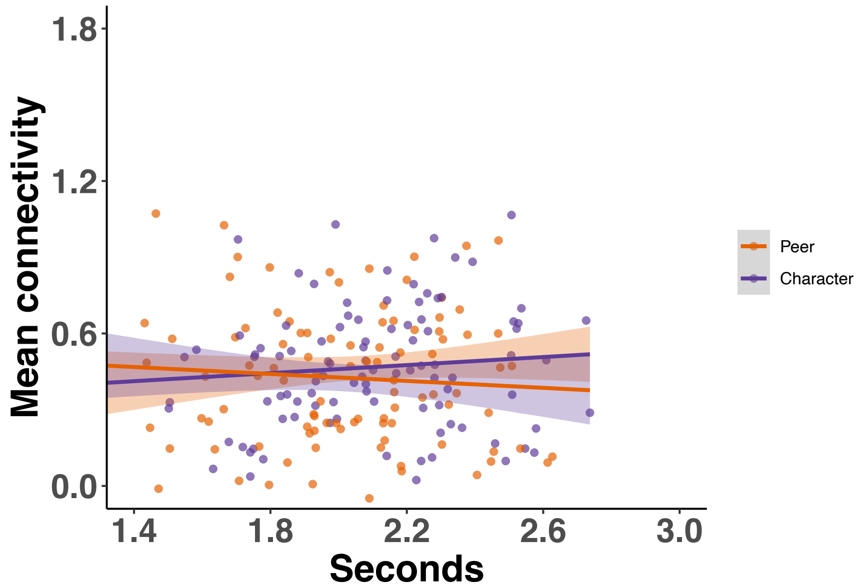

```
FC_scatterplot(mean_control_FC,"RT","salience_FC","Seconds","RT")
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```
FC_scatterplot(mean_control_FC,"RT","motor_FC","Seconds","RT")
```

```
## `geom_smooth()` using formula 'y ~ x'
```


Mean connectivity
1.8
1.2
0.6
0.0
1.4
1.8
2.2
2.6
3.0
Seconds
Peer
Character