

# ModelReport

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## Load the packages

customize theme

```
theme_new <- theme_bw() +  
  theme(panel.border = element_blank(),  
        panel.grid.major = element_blank(),  
        panel.grid.minor = element_blank(),  
        axis.line = element_line(colour = "black"),  
        strip.background = element_rect(color = "white", fill = "white"),  
        panel.grid = element_blank())  
  
options(mc.cores = parallel::detectCores())  
rstan_options (auto_write=TRUE)  
# flag for saving figures  
saveFigure = TRUE  
# flag for generating CSV  
generateSCV = TRUE  
# flag for running rstan model and saving the results  
runModels = FALSE  
# path of model result  
rstanmodelPath = 'RSTANMODELS'  
modelResultPath = paste0(rstanmodelPath, '/Version2_2')
```

## load experimental data

### RStan Models

#### Definition of the function to merge rstan result data

To further uncover the underlying structure of the prior, we hypothesize that in addition to two local priors, there is a general global prior. Participants may combine both local and global priors for the final reproduction. There are multiple possibilities for integrating those local and global priors with the sensory inputs. For examples, the sensory input could first integrate with the local prior, and then integrate with the global prior (a hierarchical local-global model, see Figure 7B in D1 proposal).

Our Hypothesis

- H1: Short and long is independent
- H3: A hierarchical local-global model In H3, global and local priors are integrated first. That means local prior is integrated with sensory input firstly, then global prior integrates with sensory input.

The sensory input ( $D_s$ ) first integrates with the local prior ( $P_L$ ) to a posterior ( $D_L$ ), which further integrates with the global prior ( $P_G$ ) to generate a final posterior for reproduction ( $D_r$ ).

- H4: Global prior (the dual integration model)

integration of local priors firstly, then integration of the global prior

Both local and global priors independently integrate with the sensory inputs to generate two posteriors ( $D_L$ ) and ( $D_G$ ), the latter two are combined together for reproduction ( $D_r$ ).

## Merg different version of model results

```
# this R script is designed for the analysis of the result of Rstan model.
mergeData <- function(cvsfiles, filename, versionlist){
  merge.data.all = {}
  for(version in versionlist){
    merge.data = {}
    dataDir <- paste0(rstanmodelPath, "/", version )
    merge.data <- read.csv(file.path(dataDir, cvsfiles[1]), header=T)
    merge.data$model = modellist[1]
    if (length(cvsfiles) >= 2) {
      for (i in 2:length(cvsfiles)){
        new.data = read.csv(file.path(dataDir, cvsfiles[i]), header=T)
        new.data$model = modellist[i]
        merge.data = rbind(merge.data,new.data)
      }
    }
    merge.data$version=version
    merge.data.all = rbind(merge.data.all, merge.data)
  }
  savedataDir <- file.path(paste0(dataDir, "/AllDat_", filename, ".csv"))
  write.csv(file=savedataDir, merge.data.all)
}
```

## H2: A hierarchical local-global model

```
stancodeH2 <- 'data {
  int<lower=0> n_s; //number of the short group baseline data points
  int<lower=0> n_l; //number of the long group baseline data points
  int<lower=0> n_mix; //number of the mix group baseline data points
  real<lower=0> Y_s[n_s]; //measured reproductive duration (short group)
  real<lower=0> X_s[n_s]; //stimulus duration (short group)
  real<lower=0> Y_l[n_l]; //measured reproductive duration (long group)
  real<lower=0> X_l[n_l]; //stimulus duration (long group)
  real<lower=0> X_mix[n_mix]; //stimulus duration (mix group)
  real<lower=0> Y_mix[n_mix]; //measured reproductive duration (mixed)
  real xmean[3]; // mean of the target duration in each group
}

parameters {
  //hyperparameters
  real<lower=0, upper =1> p_wf_s; //Weber Fraction of local prior
  real<lower=0, upper =1> wf_s; //Weber Fraction of sensory noise
  real<lower=0, upper =1> p_wf_l; //Weber Fraction of local prior
  real<lower=0, upper =1> wf_l; //Weber Fraction of sensory noise
  real<lower=0, upper =1> p_wf_m; //Weber Fraction of local prior
  real<lower=0, upper =1> wf_m; //Weber Fraction of sensory noise
  vector[n_s] mu_s; // mean of internal prior of short group
  vector[n_l] mu_l; // mean of internal prior of long group
  vector[n_mix] mu_m; // mean of global prior of mix group
  vector[n_mix] mu_m_s; // mean of local prior of mix group
  vector[n_mix] mu_m_l; // mean of local prior of mix group
}
```

```

real<lower=0, upper=9> sig_m_square;    //square of sigma of distribution of motor noise

}

transformed parameters {
    real<lower=0> sig_mix_square = p_wf_m^2 * xmean[3]^2;    //square of sigma of distribution of global prior
}

model {
    real w_s[n_s];    // weight of stimuli in short group
    real w_l[n_l];    // weight of stimuli in short group
    real p_mix[n_mix];
    real p_sig_mix[n_mix];
    real w_mix[n_mix];
    real d_mix_hat[n_mix];
    real var_mix[n_mix];
    real g_w_mix[n_mix];
    real y_mix_mean[n_mix];

    //hyperpriors
    mu_s ~ normal(xmean[1], p_wf_s^2 * xmean[1]^2);    // mean prior of short group
    mu_l ~ normal(xmean[2], p_wf_l^2 * xmean[2]^2);    // mean prior of long group
    mu_m ~ normal(xmean[3], sig_mix_square);    // mean prior of mix group (mean of global prior)
    mu_m_s ~ normal(xmean[1], p_wf_s^2 * xmean[1]^2);    // mean prior of mix group (mean of global prior)
    mu_m_l ~ normal(xmean[2], p_wf_l^2 * xmean[2]^2);    // mean prior of mix group (mean of global prior)

    //short groups
    for (i in 1:n_s)
    {
        w_s[i] = (mu_s[i]^2 * p_wf_s^2)/(mu_s[i]^2 * p_wf_s^2 + X_s[i]^2*wf_s^2);    // weight of current stimuli
        Y_s[i] ~ normal(mu_s[i] * w_s[i] + (1- w_s[i])* X_s[i], sig_m_square + (mu_s[i]^2 * p_wf_s^2 * X_s[i]^2 * p_wf_s^2) / mu_s[i]^2 * p_wf_s^2 + X_s[i]^2*wf_s^2);
    }

    //long groups
    for (i in 1:n_l)
    {
        w_l[i] = (mu_l[i]^2 * p_wf_l^2)/(mu_l[i]^2 * p_wf_l^2 + X_l[i]^2*wf_l^2);    // weight of current stimuli
        Y_l[i] ~ normal(mu_l[i] * w_l[i] + (1- w_l[i])* X_l[i], sig_m_square + (mu_l[i]^2 * p_wf_l^2 * X_l[i]^2*wf_l^2) / mu_l[i]^2 * p_wf_l^2 + X_l[i]^2*wf_l^2);
    }

    //mix groups
    for (m in 1:n_mix) {
        // H3 part1 integration of local priors firstly
        if (X_mix[m] < 1){
            p_mix[m] = mu_m_s[m];
            p_sig_mix[m] = p_mix[m] * p_wf_s;
        }else{
            p_mix[m] = mu_m_l[m];
        }
    }
}

```

```

    p_sig_mix[m] = p_mix[m] * p_wf_l;
}

w_mix[m] = p_sig_mix[m]^2 / (p_sig_mix[m]^2 + (X_mix[m]*wf_m)^2);
d_mix_hat[m] = w_mix[m] * X_mix[m] + (1-w_mix[m])*p_mix[m];

// H3 part2 posterior variances
var_mix[m] = p_sig_mix[m]^2 * (X_mix[m]*wf_m)^2 / (p_sig_mix[m]^2 + (X_mix[m]*wf_m)^2);

// H3 part3 integration of the global prior

g_w_mix[m] = sig_mix_square / (sig_mix_square+ var_mix[m]);
y_mix_mean[m] = g_w_mix[m] * d_mix_hat[m] + (1-g_w_mix[m]) * xmean[3];
Y_mix[m] ~ normal(y_mix_mean[m], sig_m_square + (sig_mix_square * var_mix[m]) / (sig_mix_square+ var_mix[m]));
}
}

generated quantities {
  vector[n_mix] ynew_mix;

  vector[n_mix] p_mix_new; // mean of internal prior of mix group
  vector[n_mix] p_sig_mix_new;
  vector[n_mix] w1_new;
  vector[n_mix] d_mix_hat_new;
  vector[n_mix] var_mix_new;
  vector[n_mix] w2_new;
  vector[n_mix] y_mix_mean_new;

  for (m in 1:n_mix) //prediction of mix group
  {
    if(X_mix[m] >= 1) {
      p_mix_new[m] = mu_m_s[m];
      p_sig_mix_new[m] = p_mix_new[m] * p_wf_s;
    }
    else{
      p_mix_new[m] = mu_m_l[m];
      p_sig_mix_new[m] = p_mix_new[m] * p_wf_l;
    }

    w1_new[m] = p_sig_mix_new[m]^2 / (p_sig_mix_new[m]^2 + (X_mix[m]*wf_m)^2);
    d_mix_hat_new[m] = w1_new[m] * X_mix[m] + (1-w1_new[m])*p_mix_new[m];

    // H3 part2 posterior variances
    var_mix_new[m] = p_sig_mix_new[m]^2 * (X_mix[m]*wf_m)^2 / (p_sig_mix_new[m]^2 + (X_mix[m]*wf_m)^2);

    // H3 part3 integration of the global prior

    w2_new[m] = sig_mix_square / (sig_mix_square+ var_mix_new[m]);
    y_mix_mean_new[m] = w2_new[m] * d_mix_hat_new[m] + (1-w2_new[m]) * xmean[3];
    ynew_mix[m] = normal_rng(y_mix_mean_new[m], sig_m_square + (sig_mix_square * var_mix_new[m]) / (sig_mix_square+ var_mix_new[m]));
  }
}

```

```

}

}
'

# compile models
if (runModels == TRUE){
stanmodelH2 <- stan_model(model_code = stancodeH2, model_name="stanmodelH2")
}

```

### H3: Global prior (the dual integration model)

```

stancodeH3 <- 'data {
int<lower=0> n_s; //number of the short group baseline data points
int<lower=0> n_l; //number of the long group baseline data points
int<lower=0> n_mix; //number of the mix group baseline data points
real<lower=0> Y_s[n_s]; //measured reproductive duration (short group)
real<lower=0> X_s[n_s]; //stimulus duration (short group)
real<lower=0> Y_l[n_l]; //measured reproductive duration (long group)
real<lower=0> X_l[n_l]; //stimulus duration (long group)
real<lower=0> X_mix[n_mix]; //stimulus duration (mix group)
real<lower=0> Y_mix[n_mix]; //measured reproductive duration (mixed)
real xmean[3]; // mean of the target duration in each group
}

parameters {
//hyperparameters
real<lower=0, upper =1> p_wf_s; //Weber Fraction of local prior
real<lower=0, upper =1> wf_s; //Weber Fraction of sensory noise
real<lower=0, upper =1> p_wf_l; //Weber Fraction of local prior
real<lower=0, upper =1> wf_l; //Weber Fraction of sensory noise
real<lower=0, upper =1> p_wf_m; //Weber Fraction of local prior
real<lower=0, upper =1> wf_m; //Weber Fraction of sensory noise
real<lower=0, upper =1> g_wf; //Weber Fraction of global prior
vector[n_s] mu_s; // mean of internal prior of short group
vector[n_l] mu_l; // mean of internal prior of long group
vector[n_mix] mu_m; // mean of global prior of mix group
vector[n_mix] mu_m_s; // mean of local prior of mix group
vector[n_mix] mu_m_l; // mean of local prior of mix group

real<lower=0, upper=9> sig_m_square; //square of sigma of distribution of motor noise
}

transformed parameters {
real<lower=0> sig_mix_square = p_wf_m^2 * xmean[3]^2; //square of sigma of distribution of global prior
}

```

```

model {
  real w_s[n_s];    // weight of stimuli in short group
  real w_l[n_l];    // weight of stimuli in short group
  real p_mix[n_mix];
  real p_sig_mix[n_mix];
  real w1[n_mix];
  real pp_mix[n_mix];
  real pp_mix_var[n_mix];
  real w2[n_mix];
  real y_mix_mean[n_mix];

  //hyperpriors
  mu_s ~ normal(xmean[1], p_wf_s^2 * xmean[1]^2); // mean prior of short group
  mu_l ~ normal(xmean[2], p_wf_l^2 * xmean[2]^2); // mean prior of long group
  mu_m ~ normal(xmean[3], sig_mix_square); // mean prior of mix group (mean of global prior)
  mu_m_s ~ normal(xmean[1], p_wf_s^2 * xmean[1]^2); // mean prior of mix group (mean of global prior)
  mu_m_l ~ normal(xmean[2], p_wf_l^2 * xmean[2]^2); // mean prior of mix group (mean of global prior)

  //short groups
  for (i in 1:n_s)
  {
    w_s[i] = (mu_s[i]^2 * p_wf_s^2)/(mu_s[i]^2 * p_wf_s^2 + X_s[i]^2*wf_s^2); // weight of current stim
    Y_s[i] ~ normal(mu_s[i] * w_s[i] + (1- w_s[i])* X_s[i], sig_m_square + (mu_s[i]^2 * p_wf_s^2 * X_s[i]
  }

  //long groups
  for (i in 1:n_l)
  {
    w_l[i] = (mu_l[i]^2 * p_wf_l^2)/(mu_l[i]^2 * p_wf_l^2 + X_l[i]^2*wf_l^2); // weight of current stim
    Y_l[i] ~ normal(mu_l[i] * w_l[i] + (1- w_l[i])* X_l[i],
    sig_m_square + (mu_l[i]^2 * p_wf_l^2 * X_l[i]^2*wf_l^2) / mu_l[i]^2 * p_wf_l^2 + X_l[i]^2*wf_l^2);
  }

  //mix groups
  for (m in 1:n_mix) {
    // first integration D_local
    if(X_mix[m] >= 1) {
      p_mix[m] = mu_m_s[m]; // local prior
      p_sig_mix[m] = p_mix[m] * p_wf_s; //sigma of D_long
    }
    else{
      p_mix[m] = mu_m_l[m]; // local prior
      p_sig_mix[m] = p_mix[m] * p_wf_l; //sigma of D_short
    }

    w1[m] = sig_mix_square^2 / (sig_mix_square^2 + p_sig_mix[m]^2);
    pp_mix[m] = p_mix[m] * w1[m] + (1- w1[m]) * xmean[3]; // integration with global prior
    pp_mix_var[m] = sig_mix_square^2* p_sig_mix[m]^2/(sig_mix_square^2 + p_sig_mix[m]^2); // integrat

```

```

        w2[m] = pp_mix_var[m] / (pp_mix_var[m] + X_mix[m]^2* g_wf^2);
        y_mix_mean[m] = w2[m] * X_mix[m] + (1-w2[m])*pp_mix[m];
        Y_mix[m] ~ normal(y_mix_mean[m],
            sig_m_square + (pp_mix_var[m] * (p_sig_mix[m])^2 ) / (pp_mix_var[m]+ (p_sig_mix[m])^2 ));
    }
}

generated quantities {
    vector[n_mix] ynew_mix;
    vector[n_mix] p_mix_new;    // mean of internal prior of mix group
    vector[n_mix] p_sig_mix_new;
    vector[n_mix] w1_new;
    vector[n_mix] pp_mix_new;
    vector[n_mix] pp_mix_var_new;
    vector[n_mix] w2_new;
    vector[n_mix] y_mix_mean_new;

    for (m in 1:n_mix)    //prediction of mix group
    {
        // first integration D_local
        if(X_mix[m] >= 1) {
            p_mix_new[m] = mu_m_s[m];    // local prior
            p_sig_mix_new[m] = p_mix_new[m] * p_wf_s;    //sigma of D_long
        }
        else{
            p_mix_new[m] = mu_m_l[m];    // local prior
            p_sig_mix_new[m] = p_mix_new[m] * p_wf_l;    //sigma of D_short
        }

        w1_new[m] = sig_mix_square^2 / (sig_mix_square^2 + p_sig_mix_new[m]^2);
        pp_mix_new[m] = p_mix_new[m] * w1_new[m] + (1- w1_new[m]) * xmean[3];    // integration with global
        pp_mix_var_new[m] = sig_mix_square^2* p_sig_mix_new[m]^2/(sig_mix_square^2 + p_sig_mix_new[m]^2);

        w2_new[m] = pp_mix_var_new[m] / (pp_mix_var_new[m] + X_mix[m]^2* g_wf^2);
        y_mix_mean_new[m] = w2_new[m] * X_mix[m] + (1-w2_new[m])*pp_mix_new[m];
        ynew_mix[m] = normal_rng(y_mix_mean_new[m],
            sig_m_square + (pp_mix_var_new[m] * (p_sig_mix_new[m])^2 ) / (pp_mix_var_new[m]+ (p_sig_mix_new[m])^2 ));
    }
}

,

# compile models
if (runModels == TRUE){
    stanmodelH3 <- stan_model(model_code = stancodeH3, model_name="stanmodelH3")
}

```

predicte the parameters of Bayesian

definisiton of the function to predicte the parameters of Bayesian by runing Rstan model

```
funFitBayesianStanH2 <- function(data, rstanModel, filename){
  Bayfit = {}
  Bayparlist = {}
  subList <- unique(data$NSub)
  fitparList = {}
  PredYlist_l = {}
  PredYlist_s = {}
  PredYlist_mix = {}
  expList <- unique(data$Exp)

  for (expName in expList) {
    subdata <- data %>% filter(valid > 0 & Exp == expName)
    subList <- unique(data$NSub)

    for (subNo in subList) {
      xmean <- data %>% filter(valid > 0 & Exp == expName & NSub == subNo ) %>% dplyr::group_by(group)

      subdata <- data %>% filter(valid > 0 & NSub == subNo & Exp == expName)
      data_s<- subdata %>% filter(group == 1) # short groups only
      data_l <- subdata %>% filter(group == 2) # long groups only
      data_mix <- subdata %>% filter(group == 3) # mixed groups
      PredY_s_list <- data_s[c('NSub','targetDur', 'RP','Exp','group')]
      PredY_l_list <- data_l[c('NSub','targetDur', 'RP','Exp','group')]
      PredY_mix_list <- data_mix[c('NSub','targetDur', 'RP','Exp','group')]
      n_s <- length(data_s$RP)
      n_l <- length(data_l$RP)
      n_mix <- length(data_mix$RP)

      stan_data = list(Y_s=data_s$RP, n_s=n_s, X_s = data_s$targetDur,
                      Y_l=data_l$RP, n_l=n_l, X_l = data_l$targetDur,
                      X_mix = data_mix$targetDur, n_mix = n_mix,
                      Y_mix = data_mix$RP,
                      "xmean" =xmean$targetMean) #data passed to stan

      # fit models
      subfit <- sampling(rstanModel, stan_data, chains = 4, iter = 4000,
                        control = list(adapt_delta = 0.99,
                                       max_treedepth = 15))

      #parameters <- c("p_wf_s","wf_s", "p_wf_l","wf_l","sig_m_square", "p_wf_m", "wf_m", "sig_mix_square")
      parameters <- c("p_wf_s","wf_s", "p_wf_l","wf_l","sig_m_square", "p_wf_m", "wf_m", "sig_mix_square")
      fitpar <- summary(subfit, pars = parameters)$summary

      list_of_draws <- rstan::extract(subfit, pars = parameters)
      p_wf_s = mean(list_of_draws$p_wf_s)
      wf_s = mean(list_of_draws$wf_s)
      p_wf_l = mean(list_of_draws$p_wf_l)
      wf_l = mean(list_of_draws$wf_l)
      wf_m = mean(list_of_draws$wf_m)
```



```

p_wf_m = mean(list_of_draws$p_wf_m)
sig_m_square = mean(list_of_draws$sig_m_square)
sig_mix_square = mean(list_of_draws$sig_mix_square)

pred_y_mix <- {}
w1_list_mix <- {}
w2_list_mix <- {}
ynew_mix_list <- list_of_draws$ynew_mix
w1_list <- list_of_draws$w1_new
w2_list <- list_of_draws$w2_new
for (n in 1:n_mix){
  pred_y_mix[n] <- mean(ynew_mix_list[,n] )
  w1_list_mix[n] <- mean(w1_list[,n] )
  w2_list_mix[n] <- mean(w2_list[,n] )
}
PredY_mix_list$predY = pred_y_mix
PredY_mix_list$w1 = w1_list_mix
PredY_mix_list$w2 = w2_list_mix
PredYlist_mix <- rbind2(PredYlist_mix, PredY_mix_list)

Baypar = data.frame(
  Nsub = subNo,
  Exp = expName,
  p_wf_s = p_wf_s,
  wf_s = wf_s,
  p_wf_l = p_wf_l,
  wf_l = wf_l,
  wf_m = wf_m,
  p_wf_m = p_wf_m,
  sig_m_square = sig_m_square,
  sig_mix_square = sig_mix_square
)
Bayparlist <- rbind2(Bayparlist, Baypar)
}
}
write.csv(Bayparlist, file = paste0(modelResultPath, "/Bayparlist_", filename, ".csv"))
write.csv(PredYlist_mix, file = paste0(modelResultPath, "/PredY_mix_", filename, ".csv"))

return(list("Bayparlist" = Bayparlist))
}

funFitBayesianStanH3 <- function(data, rstanModel, filename){
  Bayfit = {}
  Bayparlist = {}
  subList <- unique(data$NSub)
  fitparList = {}
  PredYlist_l = {}
  PredYlist_s = {}
  PredYlist_mix = {}
  expList <- unique(data$Exp)

  for (expName in expList) {
    subdata <- data %>% filter(valid > 0 & Exp == expName)

```

```

subList <- unique(data$NSub)

for (subNo in subList) {
  xmean <- data %>% filter(valid > 0 & Exp == expName & NSub == subNo ) %>% dplyr::group_by(group)

  subdata <- data %>% filter(valid > 0 & NSub == subNo & Exp == expName)
  data_s<- subdata %>% filter(group == 1) # short groups only
  data_l <- subdata %>% filter(group == 2) # long groups only
  data_mix <- subdata %>% filter(group == 3) # mixed groups
  PredY_s_list <- data_s[c('NSub','targetDur', 'RP','Exp','group')]
  PredY_l_list <- data_l[c('NSub','targetDur', 'RP','Exp','group')]
  PredY_mix_list <- data_mix[c('NSub','targetDur', 'RP','Exp','group')]
  n_s <- length(data_s$RP)
  n_l <- length(data_l$RP)
  n_mix <- length(data_mix$RP)

  stan_data = list(Y_s=data_s$RP, n_s=n_s, X_s = data_s$targetDur,
                  Y_l=data_l$RP, n_l=n_l, X_l = data_l$targetDur,
                  X_mix = data_mix$targetDur, n_mix = n_mix,
                  Y_mix = data_mix$RP,
                  "xmean" =xmean$targetMean) #data passed to stan

  # fit models
  subfit <- sampling(rstanModel, stan_data, chains = 4, iter = 4000,
                   control = list(adapt_delta = 0.99,
                                max_treedepth = 15))

  parameters <- c("g_wf", "p_wf_s","wf_s", "p_wf_l","wf_l","sig_m_square", "p_wf_m", "wf_m", "sig_l")
  fitpar <- summary(subfit, pars = parameters)$summary

  list_of_draws <- rstan::extract(subfit, pars = parameters)
  p_wf_s = mean(list_of_draws$p_wf_s)
  wf_s = mean(list_of_draws$wf_s)
  p_wf_l = mean(list_of_draws$p_wf_l)
  wf_l = mean(list_of_draws$wf_l)
  wf_m = mean(list_of_draws$wf_m)
  p_wf_m = mean(list_of_draws$p_wf_m)
  sig_m_square = mean(list_of_draws$sig_m_square)
  sig_mix_square = mean(list_of_draws$sig_mix_square)

  pred_y_mix <- {}
  w1_list_mix <- {}
  w2_list_mix <- {}
  ynew_mix_list <- list_of_draws$ynew_mix
  w1_list <- list_of_draws$w1_new
  w2_list <- list_of_draws$w2_new

  for (n in 1:n_mix){
    pred_y_mix[n] <- mean(ynew_mix_list[,n] )
  }
}

```

```

        w1_list_mix[n] <- mean(w1_list[,n] )
        w2_list_mix[n] <- mean(w2_list[,n] )
    }
    PredY_mix_list$predY = pred_y_mix
    PredY_mix_list$w1 = w1_list_mix
    PredY_mix_list$w2 = w2_list_mix
    PredYlist_mix <- rbind2(PredYlist_mix, PredY_mix_list)

    Baypar = data.frame(
        Nsub = subNo,
        Exp = expName,
        p_wf_s = p_wf_s,
        wf_s = wf_s,
        p_wf_l = p_wf_l,
        wf_l = wf_l,
        wf_m = wf_m,
        p_wf_m = p_wf_m,
        sig_m_square = sig_m_square,
        sig_mix_square = sig_mix_square
    )
    Bayparlist <- rbind2(Bayparlist, Baypar)
}
}
write.csv(Bayparlist, file = paste0(modelResultPath, "/Bayparlist_", filename, ".csv"))
write.csv(PredYlist_mix, file = paste0(modelResultPath, "/PredY_mix_", filename, ".csv"))

return(list("Bayparlist" = Bayparlist))
}

```

run the model

run H2

run H3

display the model results

Merge the Result data

To preprocess the model result data, and merge different model version data together.

```

needmerge=1
versionlist =c('Version2_2')
modellist = c('H2','H3')

if (needmerge == 1){
    predY_mix_filename <- paste0("PredY_mix_", modellist, ".csv")
    #predY_s_filename <- paste0("PredY_s_", modellist, ".csv")
    #predY_l_filename <- paste0("PredY_l_", modellist, ".csv")
    BayParlist_filename <- paste0("Bayparlist_", modellist, ".csv")
    mergeData(predY_mix_filename, 'predY_mix', versionlist)
    #mergeData(predY_s_filename, 'predY_s', versionlist)
    #mergeData(predY_l_filename, 'predY_l', versionlist)
    mergeData(BayParlist_filename, 'Bayparlist', versionlist)
}

```

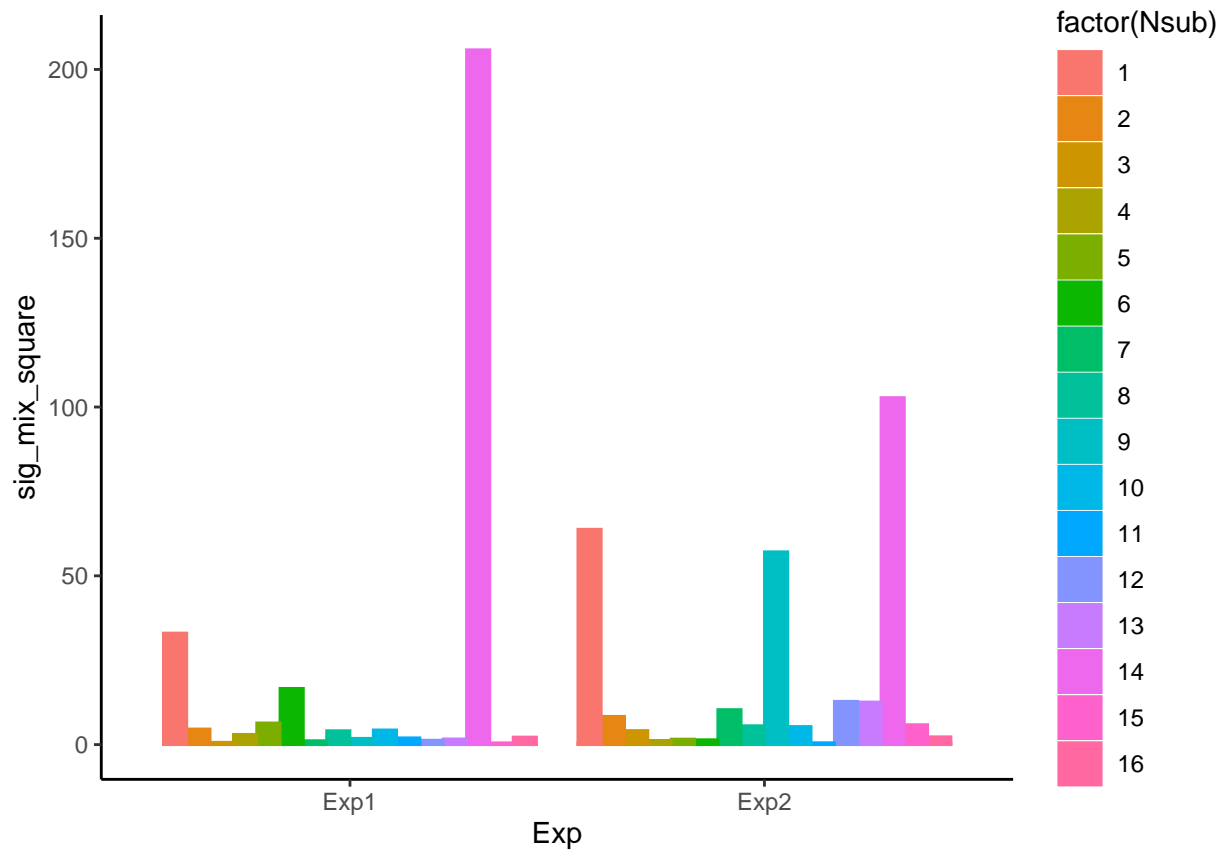
### Analysis on the Rstan model parameters

## Parameters

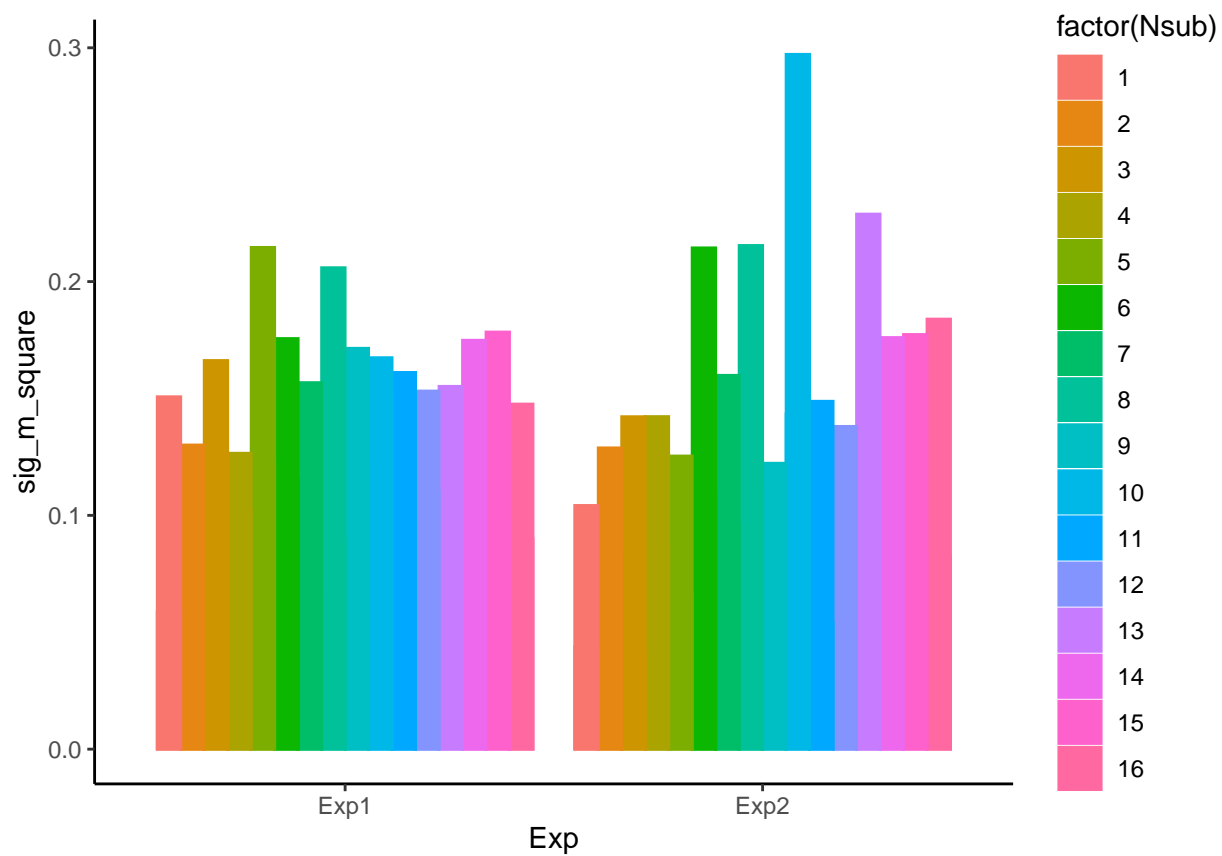
```
AllDat_Bayparlist$model <- factor(AllDat_Bayparlist$model, labels = c( "Hierarchical local-global model", "Local model", "Global model"))
m_Baypar <- group_by(AllDat_Bayparlist, Exp, Nsub, model, version) %>%
  summarize(p_wf_s = mean(p_wf_s), wf_s = mean(wf_s),
            p_wf_l = mean(p_wf_l), wf_l = mean(wf_l),
            wf_m = mean(wf_m), p_wf_m = mean(p_wf_m),
            sig_m_square = mean(sig_m_square),
            sig_mix_square = mean(sig_mix_square))

# %>%
# group_by(Exp, model, version) %>%
#   summarize(m_as = mean(m_as), n = n(), m_al = mean(m_al),
#             m_bs = mean(m_bs), m_bl = mean(m_bl),
#             m_wf = mean(m_wf))

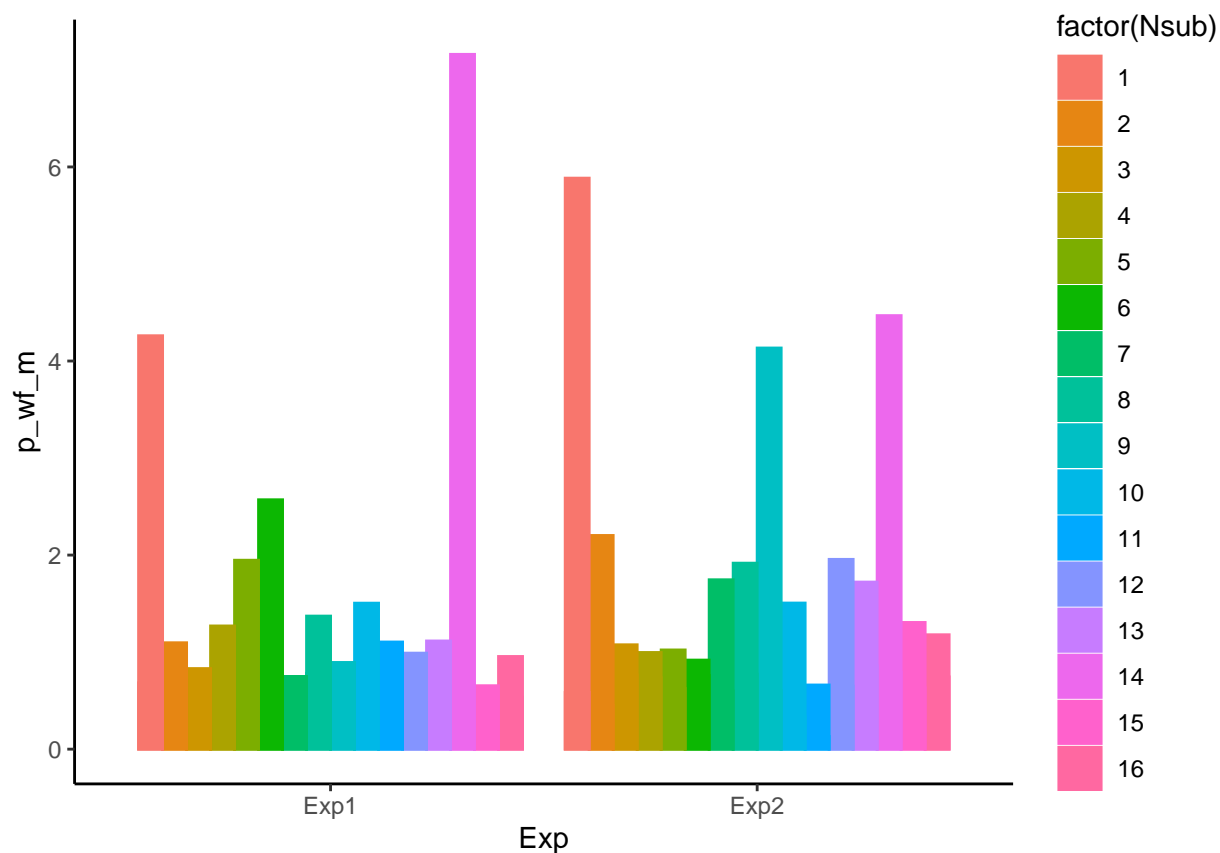
ggplot(m_Baypar, aes(x = Exp, y = sig_mix_square, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))) +
  geom_bar(stat = "identity",
           position = position_dodge()) +
  theme_new
```



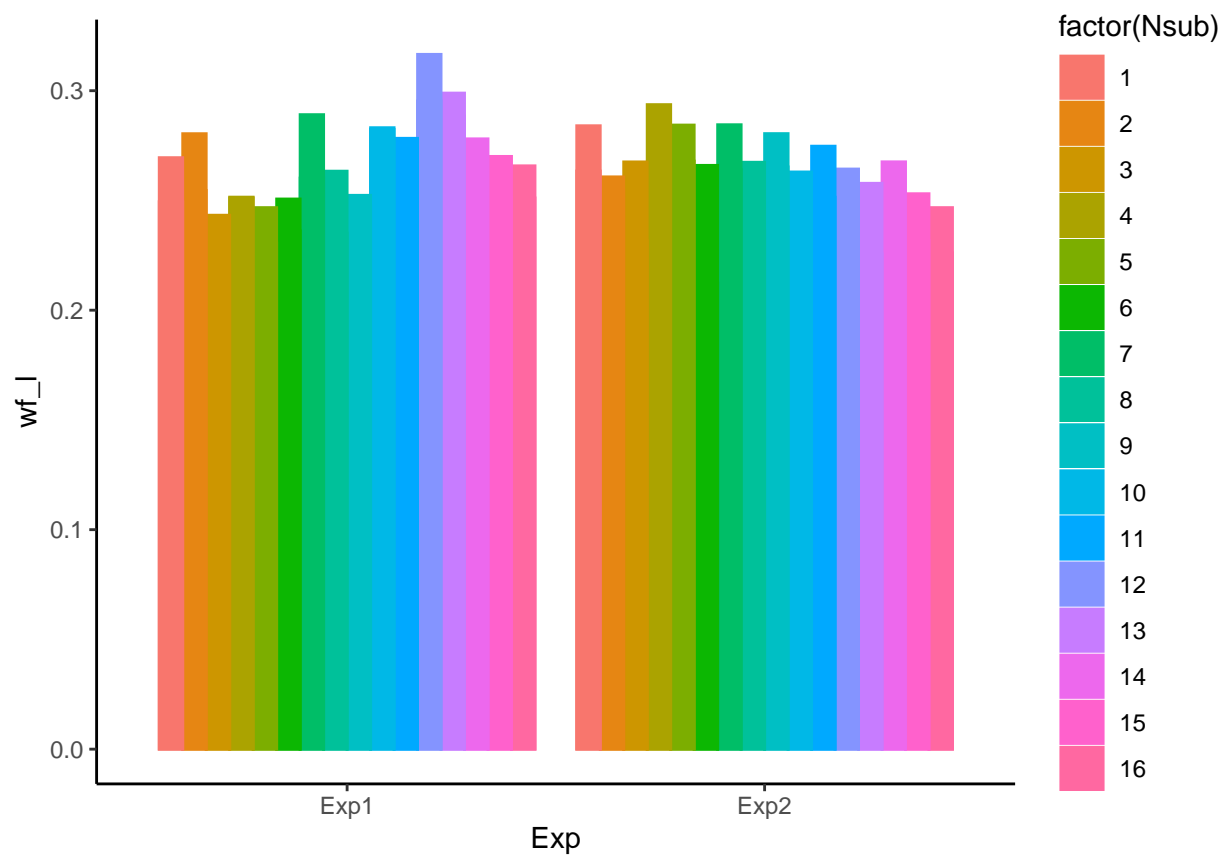
```
ggplot(m_Baypar, aes(x = Exp, y = sig_m_square, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))) +
  geom_bar(stat = "identity",
           position = position_dodge()) +
  theme_new
```



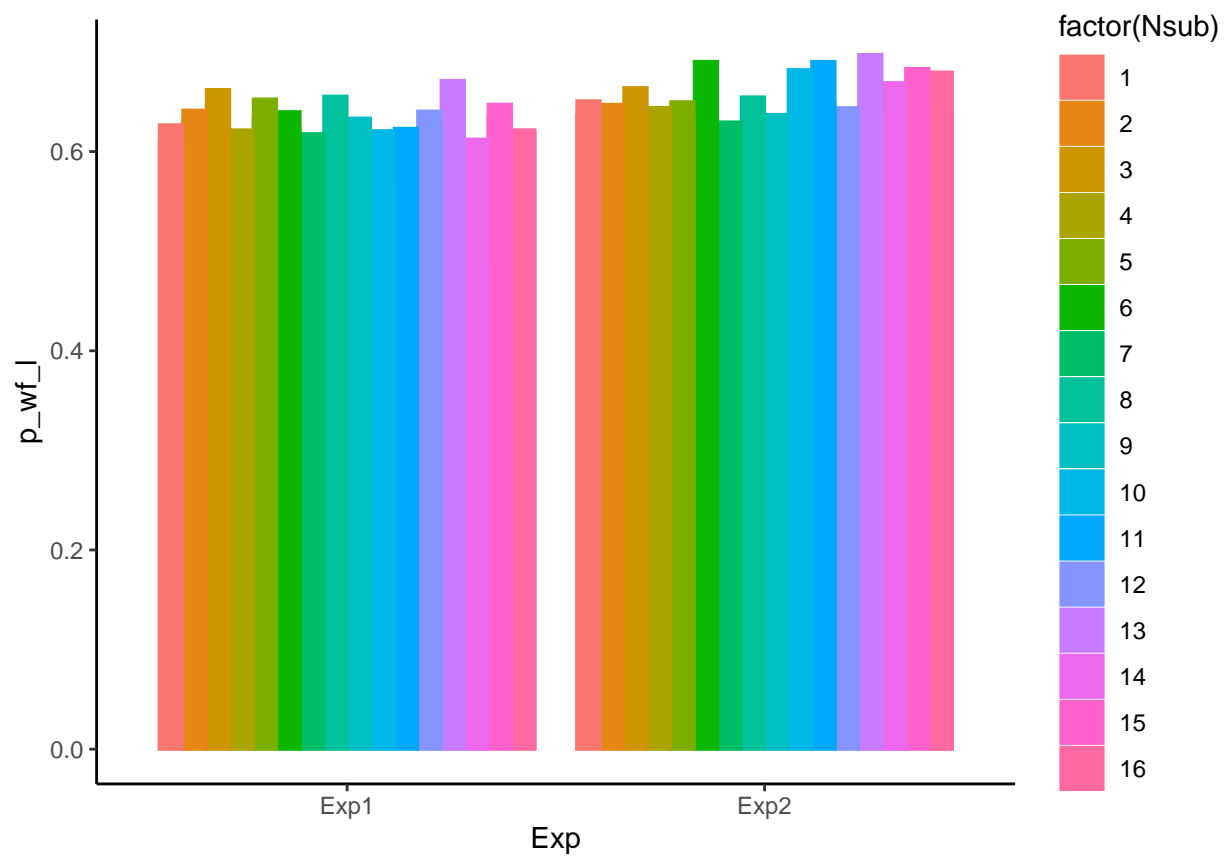
```
ggplot(m_Baypar, aes(x = Exp, y = p_wf_m, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))) +
  geom_bar(stat = "identity",
           position = position_dodge()) +
  theme_new
```



```
ggplot(m_Baypar, aes(x = Exp, y = wf_l, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))
  geom_bar(stat = "identity",
    position = position_dodge()) +
  theme_new
```

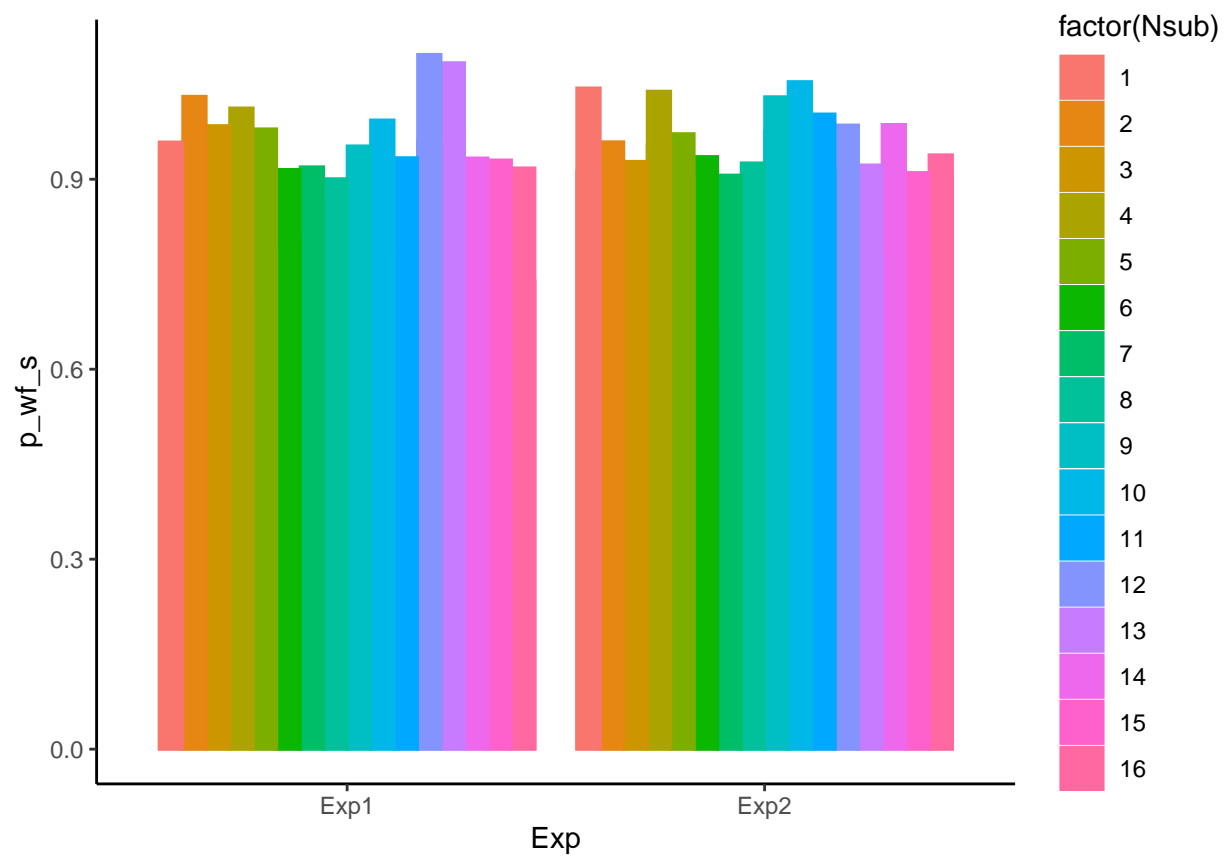


```
ggplot(m_Baypar, aes(x = Exp, y = p_wf_l, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))) +
  geom_bar(stat = "identity",
           position = position_dodge()) +
  theme_new
```

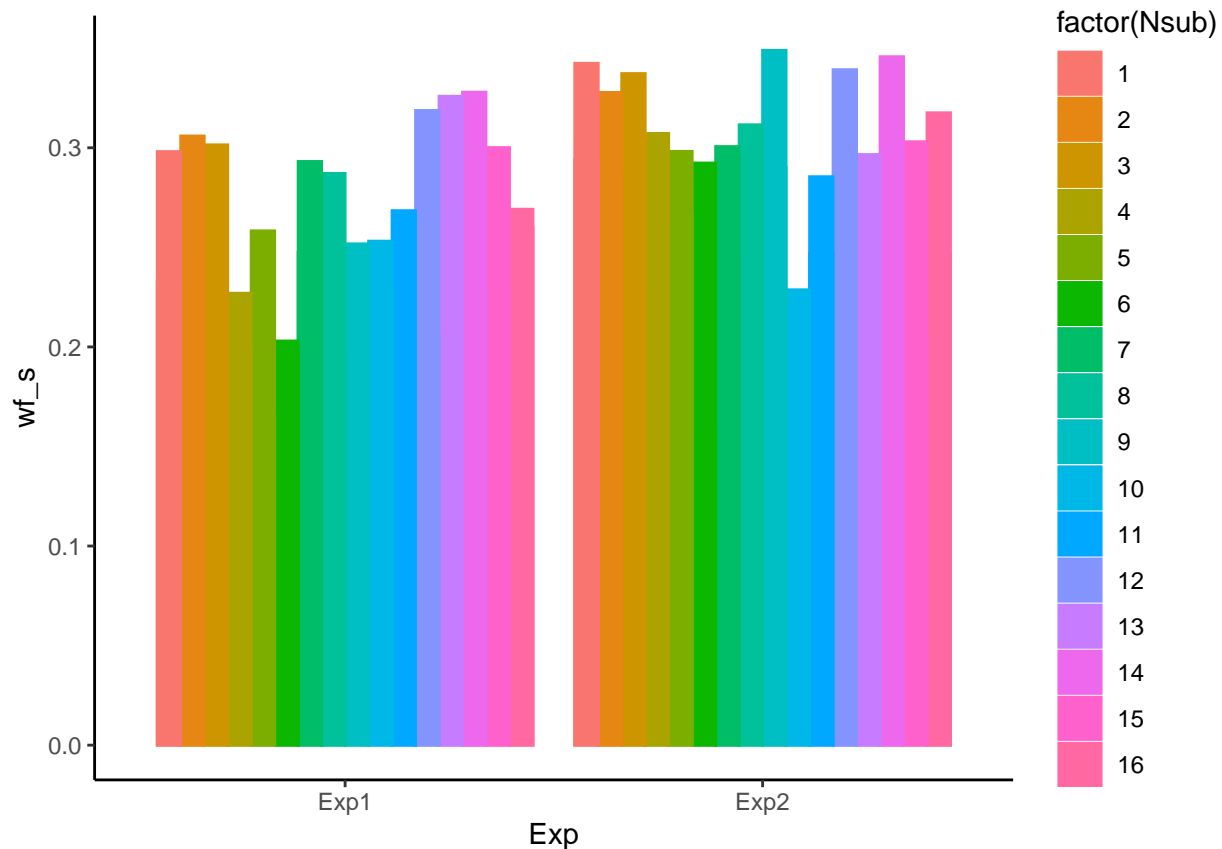


```
ggplot(m_Baypar, aes(x = Exp, y = p_wf_s, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))) +
  geom_bar(stat = "identity",
           position = position_dodge()) +
  theme_new
```





```
ggplot(m_Baypar, aes(x = Exp, y = wf_s, color = factor(Nsub), fill = factor(Nsub), group = factor(Nsub))
  geom_bar(stat = "identity",
    position = position_dodge()) +
  theme_new
```



### Prediction results (mixed block)

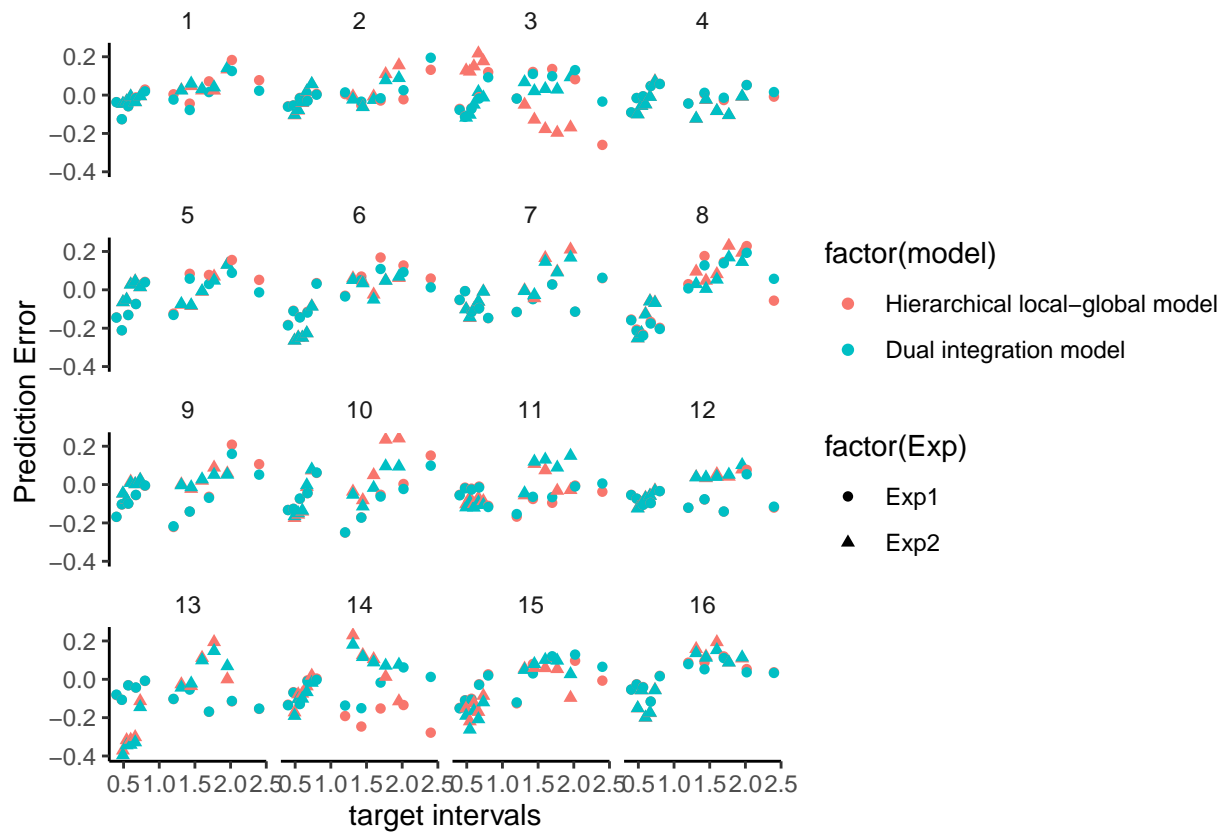
```
AllDat_predY_mix$model <- factor(AllDat_predY_mix$model, labels = c( "Hierarchical local-global model",

predY_mix <- group_by(AllDat_predY_mix, targetDur, Exp, NSub, model,version) %>%
  summarize(m_RP = mean(RP), n = n(), sd_RP = sd(RP)/ sqrt(n-1),m_predY = mean(predY), sd_predY = sd(pr
predY_mix$m_rpErr = predY_mix$m_predY - predY_mix$m_RP
predY_mix$m_relativeErr = predY_mix$m_rpErr / predY_mix$targetDur
```

The predication of mix blocks

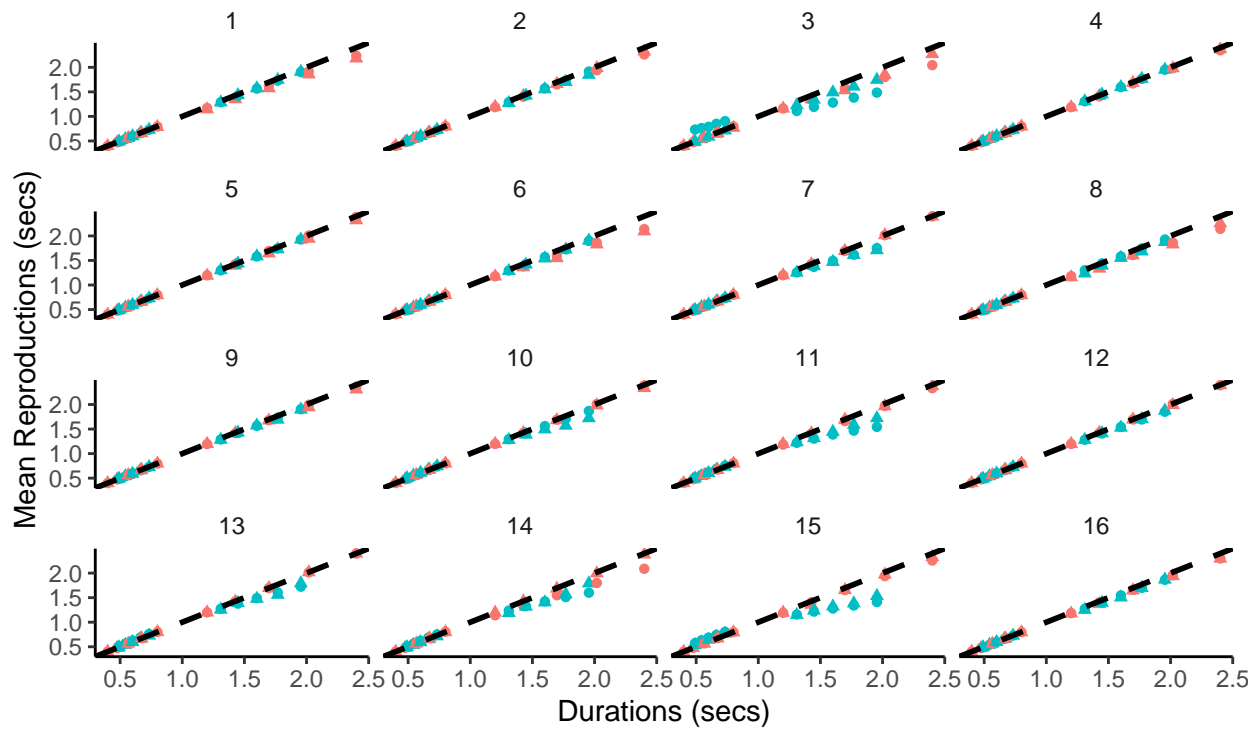
```
#plot Error in predication
fig_prederr <- ggplot(data=predY_mix, aes(x= targetDur, y=m_rpErr, shape =factor(Exp), color= factor(mo
  geom_point()+
  labs(x="target intervals", y="Prediction Error")+
  facet_wrap(~NSub) +
  theme_new

ggsave(file.path(modelResultPath,'fig_prederr_mix.png'), fig_prederr, width = 7, height = 5)
fig_prederr
```



```
#plot the average of the predicted Y under the mixed condition
fig_mpredY = ggplot(predY_mix) +
  geom_point(aes(targetDur, m_predY, group = factor(NSub), color = factor(Exp), shape = factor(model) )) +
  #geom_line(aes(targetDur, m_RP, group = factor(NSub), color = factor(NSub)), size = 1) +
  #geom_errorbar(aes(ymin = m_m_predY - se_m_predY, ymax = m_m_predY + se_m_predY), width = 0.05) +
  geom_abline(slope = 1, linetype = 2, size = 1) + # add diagonal line
  facet_wrap(~Exp) +
  guides(color = guide_legend(title = element_blank())) + # remove legend title
  theme_classic() +
  theme(strip.background = element_blank()) + # remove subtitle background
  labs(x = " Durations (secs)", y = "Mean Reproductions (secs)", size = 15) + theme(legend.position="bottom")
  facet_wrap(NSub~.)

ggsave(file.path(modelResultPath, 'fig_mpredY_mix.png'), fig_mpredY, width = 7, height = 5)
fig_mpredY
```

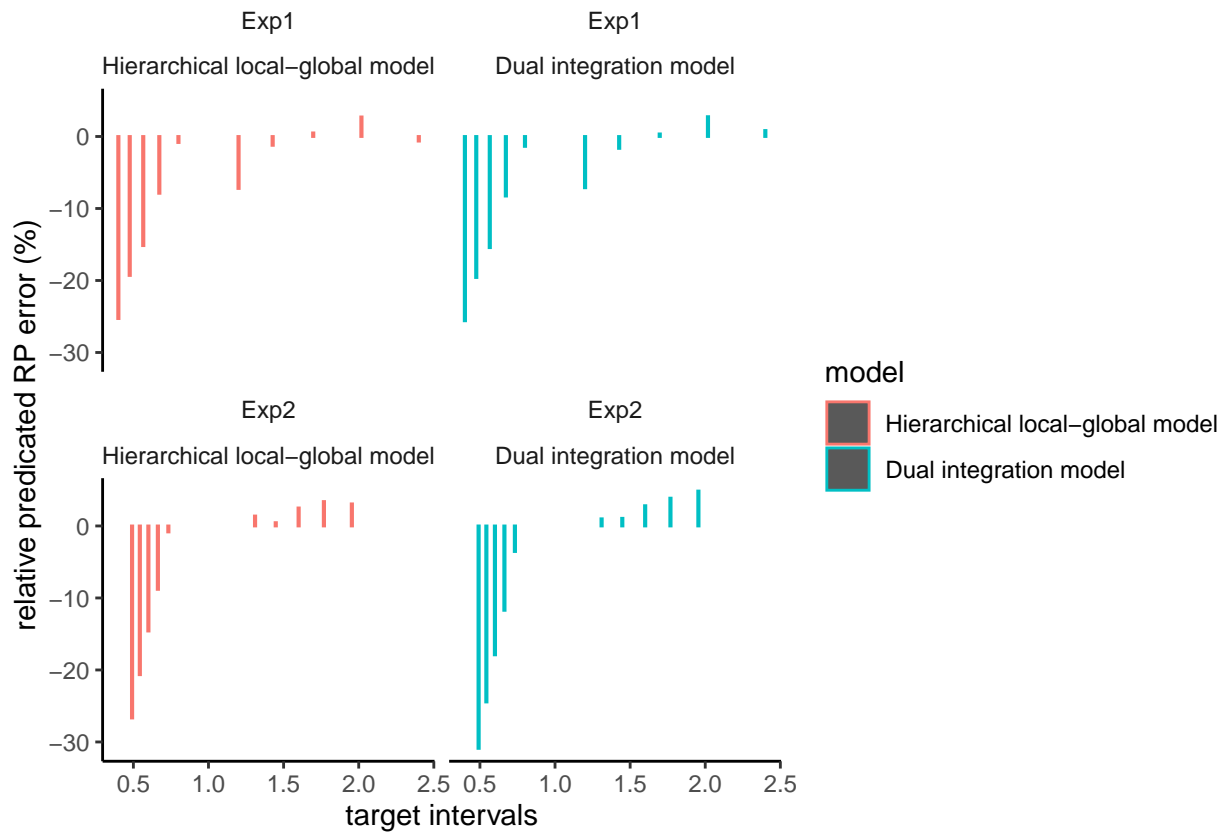


factor(model) • Hierarchical local-global model ▲ Dual integration model ● Exp1 ● Exp2

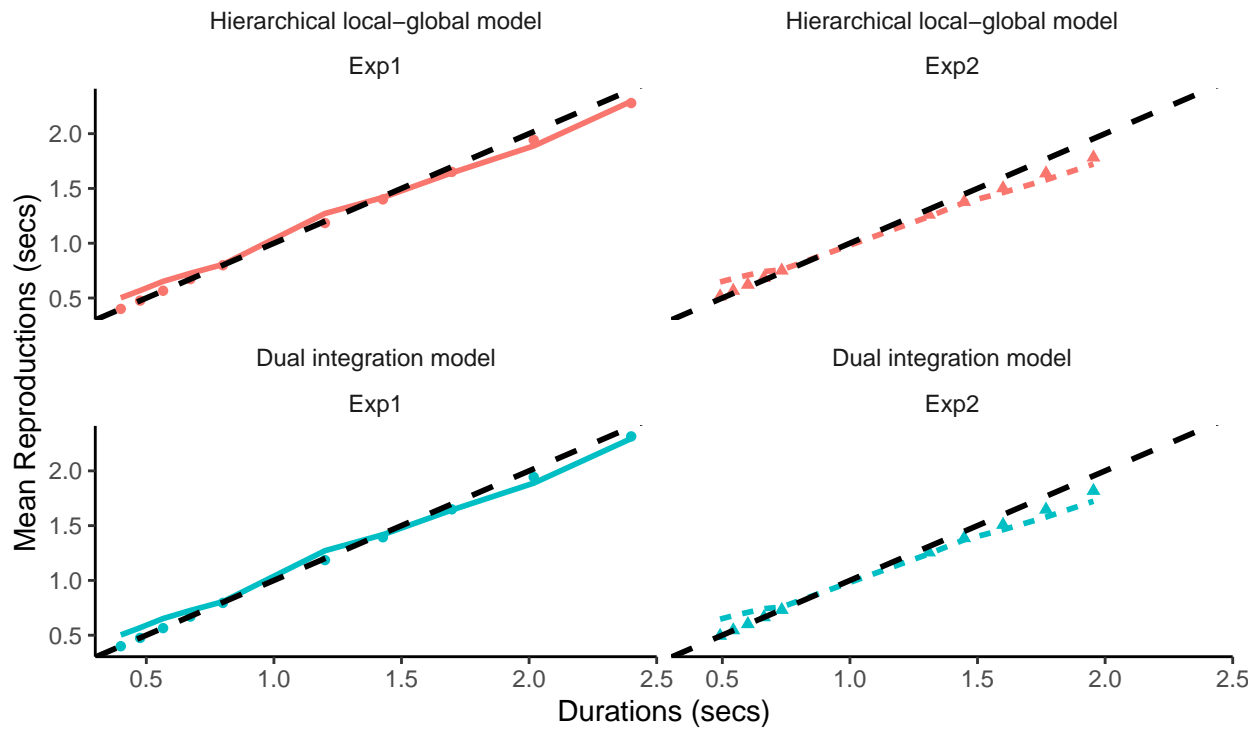
```
m_predY_mix <- predY_mix %>%
  group_by(targetDur, Exp, model, version) %>%
  summarize(
    n = n(),
    m_m_predY = mean(m_predY),
    se_m_predY = sd(m_predY) / sqrt(n - 1),
    m_m_RP = mean(m_RP),
    se_m_RP = sd(m_RP) / sqrt(n-1)
  )
m_predY_mix$m_rpErr = m_predY_mix$m_m_predY - m_predY_mix$m_m_RP
m_predY_mix$m_relativeErr = m_predY_mix$m_rpErr / m_predY_mix$targetDur

#plot relative Error for mixed blocks
fig_rerr_model <- ggplot(data=m_predY_mix, aes(x= targetDur, y=m_relativeErr*100, group = model, color = Exp)) +
  geom_bar(stat="identity") +
  labs(x="target intervals", y="relative predicated RP error (%)") +
  facet_wrap(Exp~model) +
  theme_new

ggsave(file.path(modelResultPath, 'fig_rerr_model_mix.png'), fig_rerr_model, width = 7, height = 5)
fig_rerr_model
```



```
#plot the average of the predicted Y under the mixed condition
fig_mPredY_mix = ggplot(m_predY_mix) +
  geom_point(aes(targetDur, m_m_predY, group = model, color = model, shape = factor(Exp))) +
  geom_line(aes(targetDur, m_m_RP, group = model, color = model, linetype = factor(Exp)), size = 1) +
  #geom_errorbar(aes(ymin = m_m_predY - se_m_predY, ymax = m_m_predY + se_m_predY), width = 0.05) +
  geom_abline(slope = 1, linetype = 2, size = 1) + # add diagonal line
  facet_wrap(model~Exp) +
  guides(color = guide_legend(title = element_blank())) + # remove legend title
  theme_classic() +
  theme(strip.background = element_blank()) + # remove subtitle background
  labs(x = "Durations (secs)", y = "Mean Reproductions (secs)", size = 15) + theme(legend.position="bottom")
fig_mPredY_mix
```



factor(Exp)    ●— Exp1    ▲— Exp2    ●— Hierarchical local-global model    ●— Dual integration model

```
ggsave(file.path(modelResultPath, 'fig_mPredY_mix.png'), fig_mPredY_mix, width = 7, height = 5)
```

```
predY_mix$rpErr_squared <- predY_mix$m_rpErr^2
m_predY_Err <- group_by(predY_mix, Exp, model, version) %>%
  summarize(sum_rpErr = sum(rpErr_squared),
            n = n())
```

```
fig_rpErr_model <- ggplot(m_predY_Err, aes(x = Exp, y = sum_rpErr, color = model, fill = model, group =
  geom_bar(stat = "identity",
            position = position_dodge()) +
  theme_new
```

```
ggsave(file.path(modelResultPath, 'fig_rpErr_model_mix.png'), fig_rpErr_model, width = 7, height = 5)
```

```
fig_rpErr_model
```

