06 CSI online typing: Comparison to verbal naming

Kirsten Stark 22 Mai, 2021

Load packages

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(tidyr)
library(lme4)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```
library(lmerTest)
```

```
##
## Attaching package: 'lmerTest'

## The following object is masked from 'package:lme4':
##
##     lmer

## The following object is masked from 'package:stats':
##
##     step
```

```
library(Rmisc)
```

```
## Loading required package: lattice

## Loading required package: plyr

## -------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr fi
## library(plyr); library(dplyr)

## -------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```
library(Cairo)
#library(strengejacke)
library(ggplot2)
library(sjPlot)

options(scipen=999)

rm(list = ls())
options( "encoding" = "UTF-8" )
set.seed(99)
```

Load data

Load data from both the verbal online CSI experiment and the typing online CSI experiment.

Load typing data

```
df_typing <- read.csv(here::here("data", "data_long_anonymous.csv"))
```

Select classification type (as in script 05)

```
classification_type <- "automatic"
if(classification_type == "automatic") {
  df_typing$answercode <- df_typing$answer_auto_jaro
  df_typing$correct <- df_typing$correct_auto_jaro
} else if(classification_type == "manual") {
  df_typing$answercode <- df_typing$answercode
  df_typing$correct <- df_typing$correct_manual
} else {
  print("Select a correct type!")
}
```

Load verbal data

```
load(here::here("data", "verbal_CSI", "CSI_online_verbal_df_full.RData'
df_verbal <- df_full
```

Combine both data frames into one

1. Subset relevant columns and give identical names

```
df_typing <- df_typing %>%
  dplyr::select(subject, item, category, timing.01, PosOr, correct) %>%
  dplyr::rename(RT = timing.01, Pos = PosOr) %>%
  mutate(experiment = "typing")

df_verbal <- df_verbal %>%
  dplyr::select(VP, Item, subcat, VOT, correct, Pos) %>%
  dplyr::rename(subject = VP, item = Item, category = subcat, RT = VOT
  mutate(experiment = "verbal")
```

2. Give subjects from both experiments different names

```
df_typing <- df_typing %>% mutate(subject = subject + 200)
df_verbal <- df_verbal %>% mutate(subject = subject + 100)
```

3. Put columns into correct format

```
df_typing <- df_typing %>%
  mutate(subject = as.factor(subject)) %>%
  mutate(item = as.character(item)) %>%
  mutate(category = as.factor(category)) %>%
  mutate(RT = as.numeric(RT)) %>%
  mutate(Pos = as.numeric(Pos)) %>%
  mutate(experiment = factor(experiment, levels = c("verbal", "typing"

df_verbal <- df_verbal %>%
  mutate(subject = as.factor(subject)) %>%
  mutate(item = as.character(item)) %>%
  mutate(category = as.factor(category)) %>%
  mutate(RT = as.numeric(RT)) %>%
  mutate(Pos = as.numeric(Pos)) %>%
  mutate(experiment = factor(experiment, levels = c("verbal", "typing"
```

4. Bind both data frames into one

```
df <- bind_rows(df_typing, df_verbal)
```

5. Give identical category names in both experiments

```
df <- df %>% dplyr::mutate(category = case_when(category == "Buero" ~ '
                                  category == "Gebaeude" ~ "Gebäude",
                                  category == "Gemuese" ~ "Gemüse",
                                  category ==
                                    "Koerperteile" ~ "Körperteile",
                                  category == "Kueche" ~ "Küche",
                                  category ==
                                    "Suessigkeiten" ~ "Süssigkeiten",
                                  category ==
                                    "Trinkgefaesse" ~ "Trinkgefässe",
                                  category == "Voegel" ~ "Vögel",
                                  TRUE ~ as.character(category))) %>%
  mutate(category == as.factor(category)) %>% droplevels()
table(df$category)
```

```
##
## Aufbewahrung    Bauernhof       Blumen         Büro       Filler
##          300          300          300          300         1200
##      Filler2       Fische      Gebäude       Gemüse   Heimwerker
##          600          300          300          300          300
##     Insekten  Instrumente       Jacken       Kochen  Körperteile
##          300          300          300          300          300
##         Obst    Raubtiere      Schmuck       Sitzen      Strasse Sü
##          300          300          300          300          300
## Trinkgefässe        Vögel       Wasser
##          300          300          300
```

5. Drop filler trials

```
 df <- df %>% filter(category != "Filler" &
                     category != "Filler1" & category != "Filler2") %
  droplevels()
```

6. Drop incorrect trials

```
df <- df %>% filter(!is.na(correct) & correct != 0) %>%
  dplyr::select(-correct) %>%
  droplevels()
```

7. Export combined data frame for post-hoc power plot

```
write.csv(df, here::here("data", "CSI_online_combined.csv"))
```

Descriptives

```
(descriptives <- df %>%
   Rmisc::summarySEwithin(.,"RT",idvar = "subject",
                          withinvars = "Pos",
                          betweenvars = "experiment",
                          na.rm = T))
```

```
## Automatically converting the following non-factors to factors: Pos
```

```
##    experiment Pos   N       RT       sd       se       ci
## 1      verbal   1 670 1051.558 273.0161 10.54753 20.71025
## 2      verbal   2 651 1078.679 293.7729 11.51387 22.60887
## 3      verbal   3 662 1110.344 307.4410 11.94903 23.46264
## 4      verbal   4 650 1108.178 308.8411 12.11374 23.78686
## 5      verbal   5 631 1172.052 335.0839 13.33948 26.19522
## 6      typing   1 645 1009.955 444.1659 17.48902 34.34238
## 7      typing   2 633 1085.806 553.3236 21.99264 43.18749
## 8      typing   3 638 1105.610 525.8232 20.81754 40.87930
## 9      typing   4 637 1143.374 593.4891 23.51489 46.17622
## 10     typing   5 625 1174.959 562.0187 22.48075 44.14708
```

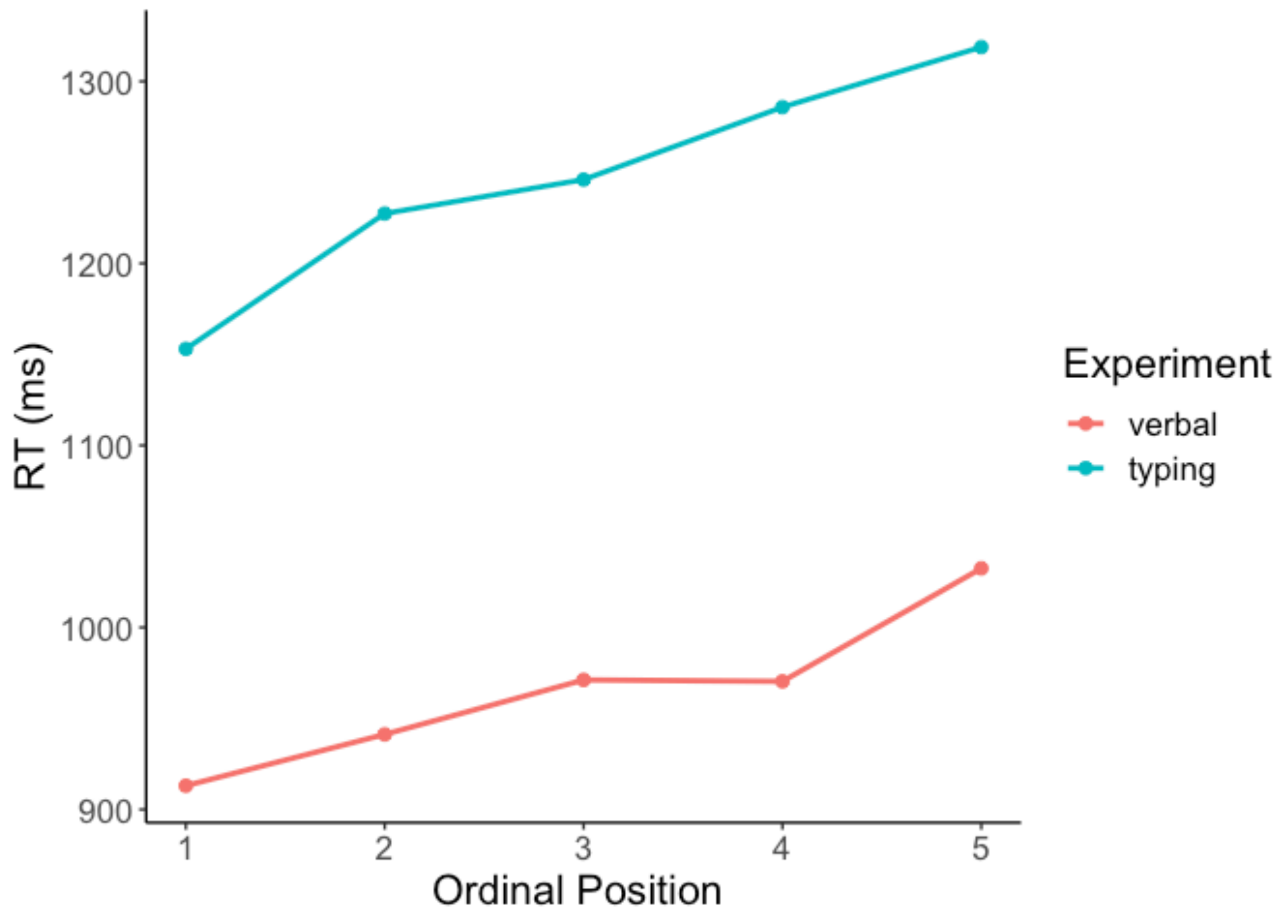
Plotting

Make plots suitable for APA format

```
apatheme <- theme_bw()+
  theme(plot.title=element_text(family="Arial",size=22,hjust = .5),
        panel.grid.major=element_blank(), panel.grid.minor=element_blar
        panel.border=element_blank(),axis.line=element_line(),
        text=element_text(family="Arial",size=16))
```

Plot RTs by ordinal position for both experiments

```
(plot <- df %>%
    ggplot(., aes(x=Pos, y=RT,
                  group=experiment, color=experiment)) +
    stat_summary(fun=mean,  geom="point", size = 2)+
    stat_summary(fun=mean,  geom="line", size = 1) +
    apatheme+
    labs(x="Ordinal Position ",y ="RT (ms)", color = "Experiment"))
```



```
filename <- "CSI_online_exp_comparison_plot_rt.pdf"
ggsave(plot, filename =
         here::here("results", "figures", filename),
       width = 18, height = 12, units = "cm",
       dpi = 300, device = cairo_pdf)
embedFonts(file = here::here("results", "figures", filename))
```

Set contrasts and convert continuous predictor variable

1. Set contrasts: Sliding difference contrast for factor experiment
   Subsequent factor levels are being compared to each other, i.e. verbal-typing, the intercept being the grand mean.

```
# define sliding difference contrast for factor experiment:
# contrast is verbal - typing, intercept being the grand mean
levels(df$experiment)
```

```
## [1] "verbal" "typing"
```

```
contrasts(df$experiment) <- MASS::contr.sdif(2)
```

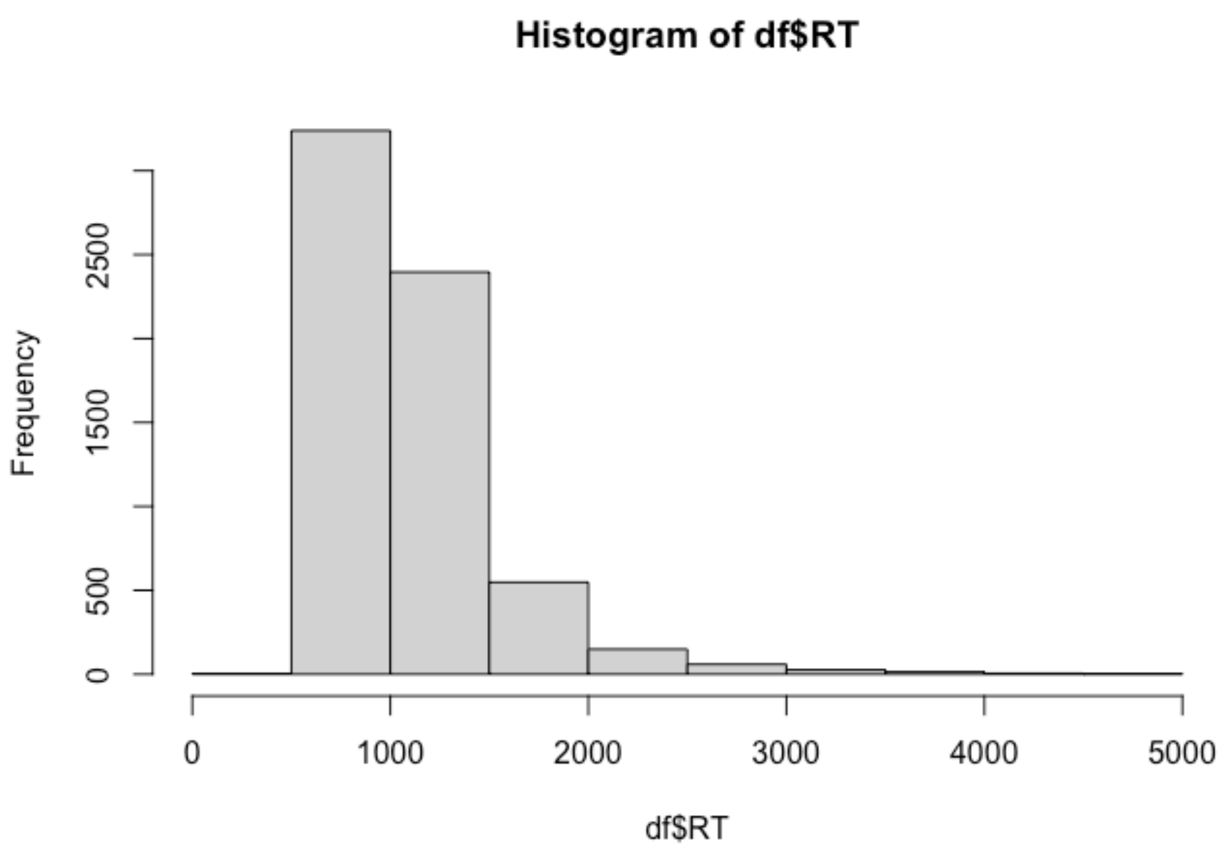
2. Center the continuous predictor variable position around zero (ordinal contrast with five levels)

```
df$Pos.cont <- scale(as.numeric(as.character(df$Pos)),
                       center = T, scale = F)
# table(df$Pos.cont)
# mean(df$Pos.cont)
```

Check distribution of data

Are the data normally distributed or does a gamma distribution fit the data better?
Histogram of the reaction time data

```
hist(df$RT)
```



Check fit of normal vs gamma distribution in histograms, q-q-plots and using objective criteria:

1) Fit normal and gamma distributions to the reaction time data

```
library(fitdistrplus)
```

```
## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

## Loading required package: survival
```

```
fit.normal<- fitdist(df$RT, distr = "norm", method = "mle")
summary(fit.normal)
```

```
## Fitting of the distribution ' norm ' by maximum likelihood
## Parameters :
##       estimate Std. Error
## mean 1103.4596   5.389018
## sd    432.5251   3.810561
## Loglikelihood:  -48241.43   AIC:  96486.85   BIC:  96500.39
## Correlation matrix:
##      mean sd
## mean    1  0
## sd      0  1
```

```
#plot(fit.normal)
```

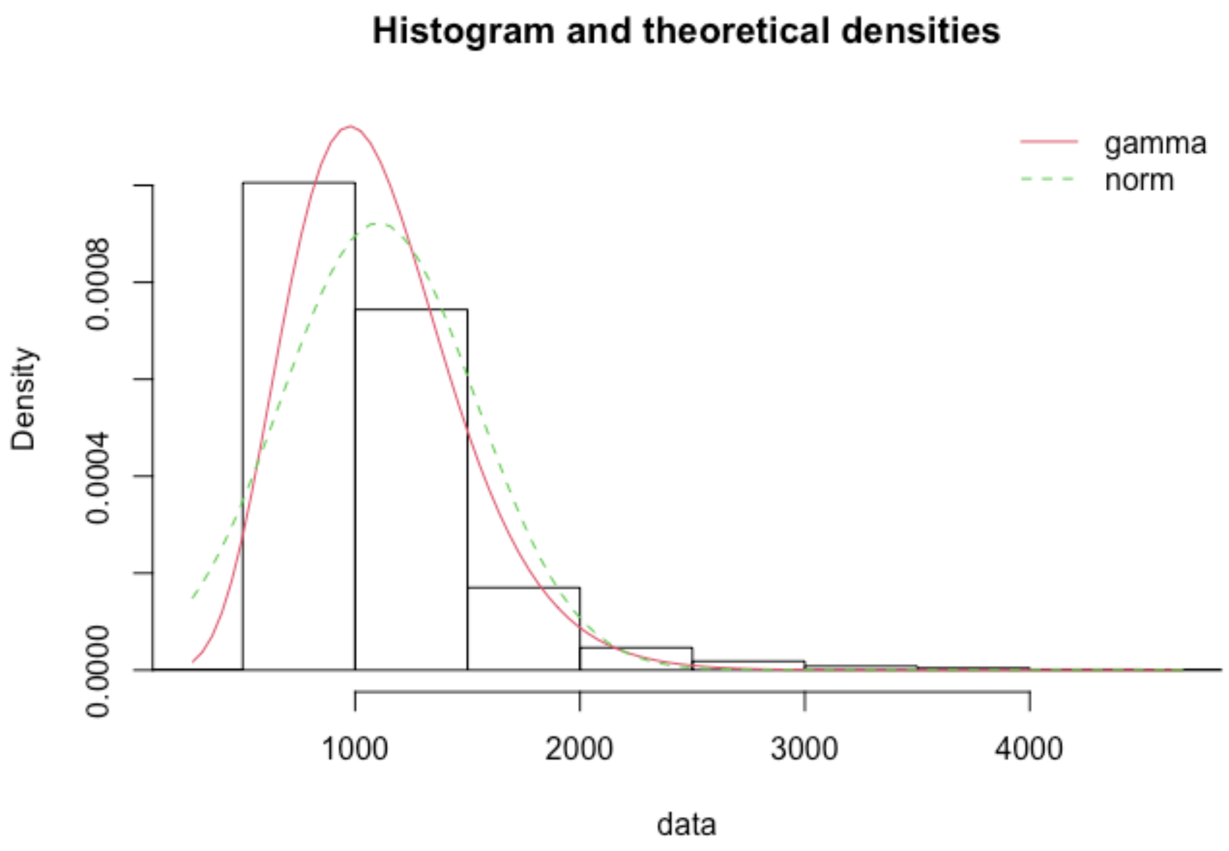
```
fit.gamma <- fitdist(df$RT, distr = "gamma", method = "mle")
summary(fit.gamma)
```

```
## Fitting of the distribution ' gamma ' by maximum likelihood
## Parameters :
##          estimate   Std. Error
## shape 8.714704899 0.1288279543
## rate  0.007897942 0.0001182167
## Loglikelihood:  -47047.64   AIC:  94099.27   BIC:  94112.81
## Correlation matrix:
##           shape      rate
## shape 1.0000000 0.9607663
## rate  0.9607663 1.0000000
```

```
#plot(fit.gamma)
```

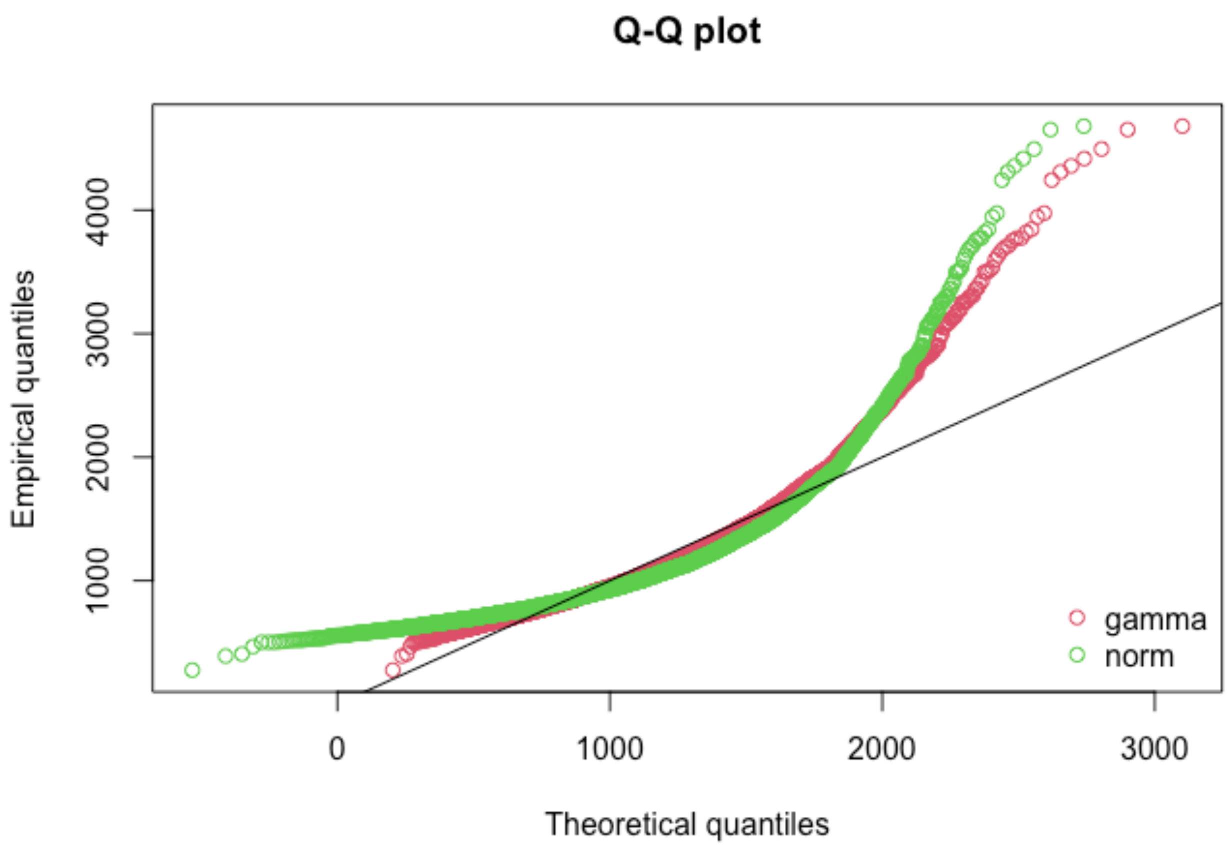
2. Compare the fit of the two distributions
   Visually compare fit of both distributions in histogram

```
denscomp(list(fit.gamma, fit.normal))
```



Visually compare fit of both distributions in Q-Q-plots

```
qqcomp(list(fit.gamma, fit.normal))
```



Compare information criteria

```
gofstat(list(fit.gamma, fit.normal),
        fitnames = c("Gamma", "Normal"))
```

```
## Goodness-of-fit statistics
##                                     Gamma      Normal
## Kolmogorov-Smirnov statistic   0.08526673   0.1349558
## Cramer-von Mises statistic    16.64374270  45.0123565
## Anderson-Darling statistic   100.97376437 263.8788753
##
## Goodness-of-fit criteria
##                                   Gamma   Normal
## Akaike's Information Criterion 94099.27 96486.85
## Bayesian Information Criterion 94112.81 96500.39
```

Conclusion: Both the visual inspection and the objective criteria suggest that a gamma distribution fits the data better. Therefore, we fit a Gamma distribution in a GLMM with the continuous predictor ordinal position (Pos.cont), the factorial predictor (experiment), and their interaction. We compute the maximal random effects structure.

Interferential statistics: GLMM with predictors Pos.cont and experiment

```
m1 <- afex::lmer_alt(RT ~ Pos.cont*experiment +
               (Pos.cont||subject) +(Pos.cont*experiment||category),
            data = df,
           family =Gamma(link ="identity"),
           control=glmerControl(optimizer = "bobyqa", optCtrl = list(
```

```
## Registered S3 methods overwritten by 'car':
##   method                          from
##   influence.merMod                lme4
##   cooks.distance.influence.merMod lme4
##   dfbeta.influence.merMod         lme4
##   dfbetas.influence.merMod        lme4
```

```
summary(m1)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: Gamma  ( identity )
## Formula: RT ~ Pos.cont * experiment + (1 + re1.Pos.cont || subject)
##     (1 + re2.Pos.cont + re2.experiment2.1 + re2.Pos.cont_by_experime
##         category)
##    Data: data
## Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun =
##
##      AIC      BIC   logLik deviance df.resid
##  91500.8  91575.3 -45739.4  91478.8     6431
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0610 -0.6089 -0.2349  0.3176  9.4786
##
## Random effects:
##  Groups     Name                             Variance  Std.Dev.
##  subject    (Intercept)                      5632.0470 75.0470
##  subject.1  re1.Pos.cont                      418.1712 20.4492
##  category   (Intercept)                      4510.9510 67.1636
##  category.1 re2.Pos.cont                   247.0792 15.7188
##  category.2 re2.experiment2.1             4224.1364 64.9934
##  category.3 re2.Pos.cont_by_experiment2.1  502.1754 22.4093
##  Residual                                    0.0988  0.3143
## Number of obs: 6442, groups:  subject, 60; category, 24
##
## Fixed effects:
##                          Estimate Std. Error t value             Pr(>
## (Intercept)              1153.267      4.780 241.287 < 0.00000000000
## Pos.cont                   34.353      4.735   7.256     0.0000000000
## experiment2-1             289.641      4.839  59.850 < 0.00000000000
## Pos.cont:experiment2-1     11.365      7.184   1.582                0.
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Ps.cnt exp2-1
## Pos.cont     0.177
## expermnt2-1 -0.221 -0.193
## Ps.cnt:x2-1 -0.278 -0.161  0.115
```

```
# save model output
tab_model(m1,transform = NULL,
          show.re.var = F, show.stat = T,show.r2 = F,show.icc = F,
          title = "GLMM (Gamma distribution)",
          pred.labels = c("(Intercept)", "Ordinal Position",
                          "Experiment", "(Ordinal Position) x
                          \n (Experiment)"),
          wrap.labels = 10,
          dv.labels = "Typing Onset Latency",
          #string.pred = "",
          string.stat = "t-Value",
          file = here::here("results", "tables",
                            "CSI_online_experiment_comparison_glmm_con
```

GLMM (Gamma distribution)

	Typing Onset Latency			
Predictors	*Estimates*	*CI*	*t-Value*	*p*
(Intercept)	1153.27	1143.90 – 1162.64	241.29	**<0.001**

Ordinal Position	34.35	25.07 – 43.63	7.26	**<0.001**
Experiment	289.64	280.16 – 299.13	59.85	**<0.001**
(Ordinal Position) x (Experiment)	11.37	-2.71 – 25.44	1.58	0.114
N $_{subject}$	60			
N $_{category}$	24			
Observations	6442			