Nepal Earthquake Intervention Analysis

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Nepal Earthquake Intervention Study

Getting the data in

x results of disaster-preparedness and mental health intervention study conducted following an earthquake event in Nepal. First we load the required R packages, load the STATA file and inspect its structure. Major heavy-lifting of data cleaning, feature generation, and converstion to long-format was conducted using SPSS and STATA (see asssociated .sps SPSS syntax files and .do STATA scripts). For example, corrections to ordinal variables which were incorrectly binarized and generation of mental health / behavioral scale scores from means or sums of indivdiual items were done using these software.

```
melt_data_suffix <- function(var_name) {
  new_var <- vector(mode = "numeric", length = nrow(data))
  new_var[data$timePoint == '1'] <- as.numeric(data[[paste0(var_name, '1')]][data$timePoint == '1'])
  new_var[data$timePoint == '2'] <- as.numeric(data[[paste0(var_name, '2')]][data$timePoint == '2'])
  new_var[data$timePoint == '3'] <- as.numeric(data[[paste0(var_name, '3')]][data$timePoint == '3'])
  return(new_var)
}

melt_data_prefix <- function(var_name) {
  var_name <- substr(var_name, 3, nchar(var_name))
  new_var <- vector(mode = "numeric", length = nrow(data))
  new_var <- as.numeric(data[[paste0('T1', var_name)]])
  new_var[data$timePoint == '1'] <- as.numeric(data[[paste0('T1',var_name)]][data$timePoint == '1'])
  new_var[data$timePoint == '2'] <- as.numeric(data[[paste0('T2',var_name)]][data$timePoint == '2'])
  new_var[data$timePoint == '3'] <- as.numeric(data[[paste0('T3',var_name)]][data$timePoint == '3'])
  return(new_var)
}
```

```
library(haven)
library(ggplot2)
library(dplyr)
library(scales)
library(lme4)
library(lsmeans)
library(car)
library(RLRsim)
library(texreg)
library(magrittr)
library(xtable)
library(lmerTest)
library(ordinal)
library(RVAideMemoire)
library(reporttools)
#source("https://raw.github.com/glmmTMB/glmmTMB/master/misc/lsmeans.R")
setwd("C:/Users/ajame/Dropbox/Alex - Nepal/EQ data")
data <- read_dta("Kathmandu_Valley_NEPAL_all_times WITH LABELS reshaped.dta")
```

We filter out subjects that did not participate in the intervention at any time point (this is a stepped-wedge design) by selecting only subjects that have positive values in the associated indicator variables, and then convert data to factor variables where applicable. We also create a variable, interventionPlotting, that corrects the intervention effect variable (interventionT) to make it more useful for our plotting. We'll also reshape/melt some of the variables manually to long format (across time points).

```
data %<>% as_factor(data)
data %<>% rename(city = T1Citycode, gender = T1Gender)
data$timePoint <- factor(data$timePoint)
data$interventPlotting <- data$interventionT
data$interventPlotting[data$city=='Chhaling' & data$timePoint=='1'] <- 'Intervention'
data$interventPlotting[data$city=='Tathali' & data$timePoint=='2'] <- 'Intervention'
data$phqMean6_T <- data$phqMean6_T + 1

to_melt_prefix <- c('T1DisMH1Anxiousdep', 'T1DisMH2Avoid')

for(i in to_melt_prefix){
  data[[paste0(substr(i,3,nchar(i)), '_T')]] <- melt_data_prefix(i)
}

filtered <- data %>% filter(T2Interventionparticipant == 1 | T3Interventionparticipant == 1)
```

First let's get descriptive statistics on disaster preparedness items.

```
T1_DP_vars <- filtered %>% filter(timePoint == "1") %>% select(T1Disprep1futureEQrevCoded, T1Disprep2mor

T2_DP_vars <- filtered %>% filter(timePoint == "2") %>% select(T2Disprep1futureEQrevCoded, T2Disprep2mor

T3_DP_vars <- filtered %>% filter(timePoint == "3") %>% select(T3Disprep1futureEQrevCoded, T3Disprep2mor
```

```
tableNominal(vars = as.data.frame(T1_DP_vars), lab = "tabdp1", longtable = TRUE, cumsum = FALSE, cap =
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:44:53 2017

Variable	Levels	n	%
T1Disprep1futureEQrevCoded	1	11	5.4
	2	20	9.9
	3	127	62.9
	4	44	21.8
	all	202	100.0
T1Disprep2monsoonprepfixedrev	1	19	9.4
	2	12	5.9
	3	132	65.3
	4	39	19.3
	all	202	100.0
T1Disprep3Supplykit	0	178	88.1
	1	24	11.9
	all	202	100.0
T1Disprep3Foodwater	0	76	37.6
	1	126	62.4
	all	202	100.0
T1Disprep3Docs	0	28	13.9
	1	174	86.1
	all	202	100.0
T1Disprep3Dwelling	0	30	14.8
	1	172	85.2
	all	202	100.0
T1Disprep3Furn	0	65	32.2

	1	137	67.8
	all	202	100.0
T1Disprep3Famplan	0	105	52.0
	1	97	48.0
	all	202	100.0
T1Disprep3Commplan	0	34	16.8
	1	168	83.2
	all	202	100.0

Table 1: Descriptive statistics of disaster preparation behaviors time 1 questions

```
tableNominal(vars = as.data.frame(T2_DP_vars), lab = "tabdp2", longtable = TRUE, cumsum = FALSE, cap =
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:44:54 2017

Variable	**Levels**	**n**	%
T2Disprep1futureEQrevCoded	1	9	4.5
	2	9	4.5
	3	118	58.7
	4	65	32.3
	all	201	100.0
T2Disprep2monsoonprepfixedrev	1	12	6.0
	2	15	7.5
	3	115	57.2
	4	59	29.4
	all	201	100.0
T2Disprep3Supplykit	0	147	73.1
	1	54	26.9
	all	201	100.0
T2Disprep3Foodwater	0	44	21.9
	1	157	78.1
	all	201	100.0
T2Disprep3Docs	0	8	4.0
	1	193	96.0
	all	201	100.0
T2Disprep3Dwelling	0	25	12.4
	1	176	87.6
	all	201	100.0
T2Disprep3Furn	0	42	20.9
	1	159	79.1
	all	201	100.0
T2Disprep3Famplan	0	77	38.3
	1	124	61.7
	all	201	100.0
T2Disprep3Commplan	0	5	2.5
	1	196	97.5
	all	201	100.0

Table 2: Descriptive statistics of disaster preparation behaviors time 2 questions

```
tableNominal(vars = as.data.frame(T3_DP_vars), lab = "tabdp3", longtable = TRUE, cumsum = FALSE, cap =
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:44:54 2017

Variable	**Levels**	**n**	%
T3Disprep1futureEQrevCoded	1	1	0.5
	2	8	4.0
	3	119	58.9
	4	74	36.6
	all	202	100.0
T3Disprep2monsoonprepfixedrev	1	2	1.0

	2	8	4.0
	3	110	54.5
	4	82	40.6
	all	202	100.0
T3Disprep3Supplykit	0	97	48.0
	1	105	52.0
	all	202	100.0
T3Disprep3Foodwater	0	25	12.4
	1	177	87.6
	all	202	100.0
T3Disprep3Docs	0	2	1.0
	1	200	99.0
	all	202	100.0
T3Disprep3Dwelling	0	7	3.5
	1	195	96.5
	all	202	100.0
T3Disprep3Furn	0	22	10.9
	1	180	89.1
	all	202	100.0
T3Disprep3Famplan	0	41	20.3
	1	161	79.7
	all	202	100.0
T3Disprep3Commplan	0	3	1.5
	1	199	98.5
	all	202	100.0

Table 3: Descriptive statistics of disaster preparation behaviors time 3 questions

Now let's perform a Cronbach's alpha analysis on disaster preparedness items - we can use the alphas if item is omitted to detect outliers.

```
psych::alpha(x = select(T1_DP_vars, -T1Disprep1futureEQrevCoded, -T1Disprep2monsoonprepfixedrev), cumula
```

```
##
## Reliability analysis
## Call: psych::alpha(x = select(T1_DP_vars, -T1Disprep1futureEQrevCoded,
##     -T1Disprep2monsoonprepfixedrev), cumulative = TRUE)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd
##       0.57      0.58    0.58      0.16 1.4 0.046  4.4 1.6
##
##  lower alpha upper     95% confidence boundaries
## 0.48 0.57 0.66
##
##  Reliability if an item is dropped:
##                      raw_alpha std.alpha G6(smc) average_r S/N alpha se
## T1Disprep3Supplykit      0.55      0.57    0.57      0.18 1.3    0.049
## T1Disprep3Foodwater      0.49      0.51    0.51      0.15 1.0    0.056
## T1Disprep3Docs           0.51      0.52    0.51      0.15 1.1    0.053
## T1Disprep3Dwelling       0.50      0.51    0.50      0.15 1.0    0.054
## T1Disprep3Furn           0.51      0.51    0.49      0.15 1.1    0.052
## T1Disprep3Famplan        0.59      0.59    0.57      0.19 1.5    0.043
## T1Disprep3Commplan       0.55      0.57    0.56      0.18 1.3    0.049
##
##  Item statistics
##                        n raw.r std.r r.cor r.drop mean   sd
## T1Disprep3Supplykit  202  0.41  0.46  0.28   0.22 0.12 0.32
## T1Disprep3Foodwater  202  0.64  0.60  0.50   0.39 0.62 0.49
```

```
## T1Disprep3Docs      202  0.55  0.59  0.48   0.36 0.86 0.35
## T1Disprep3Dwelling  202  0.58  0.61  0.53   0.39 0.85 0.36
## T1Disprep3Furn      202  0.60  0.59  0.52   0.34 0.68 0.47
## T1Disprep3Famplan   202  0.47  0.41  0.23   0.15 0.48 0.50
## T1Disprep3Commplan  202  0.46  0.47  0.30   0.24 0.83 0.38
##
## Non missing response frequency for each item
##                        0    1 miss
## T1Disprep3Supplykit 0.88 0.12    0
## T1Disprep3Foodwater 0.38 0.62    0
## T1Disprep3Docs      0.14 0.86    0
## T1Disprep3Dwelling  0.15 0.85    0
## T1Disprep3Furn      0.32 0.68    0
## T1Disprep3Famplan   0.52 0.48    0
## T1Disprep3Commplan  0.17 0.83    0
```

```
psych::alpha(x = select(T2_DP_vars, -T2Disprep1futureEQrevCoded, -T2Disprep2monsoonprepfixedrev), cumula
```

```
##
## Reliability analysis
## Call: psych::alpha(x = select(T2_DP_vars, -T2Disprep1futureEQrevCoded,
##     -T2Disprep2monsoonprepfixedrev), cumulative = TRUE)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd
##       0.67      0.68    0.68      0.23 2.1 0.032  5.2 1.6
##
##  lower alpha upper     95% confidence boundaries
## 0.61 0.67 0.73
##
##  Reliability if an item is dropped:
##                     raw_alpha std.alpha G6(smc) average_r S/N alpha se
## T2Disprep3Supplykit      0.64      0.66    0.65      0.24 1.9    0.036
## T2Disprep3Foodwater      0.62      0.63    0.62      0.22 1.7    0.038
## T2Disprep3Docs           0.65      0.62    0.61      0.21 1.6    0.035
## T2Disprep3Dwelling       0.61      0.62    0.61      0.21 1.6    0.038
## T2Disprep3Furn           0.63      0.63    0.63      0.22 1.7    0.036
## T2Disprep3Famplan        0.61      0.62    0.61      0.21 1.6    0.040
## T2Disprep3Commplan       0.69      0.70    0.68      0.28 2.4    0.033
##
##  Item statistics
##                        n raw.r std.r r.cor r.drop mean   sd
## T2Disprep3Supplykit 201  0.62  0.54  0.41   0.38 0.27 0.44
## T2Disprep3Foodwater 201  0.65  0.62  0.53   0.44 0.78 0.41
## T2Disprep3Docs      201  0.52  0.64  0.56   0.41 0.96 0.20
## T2Disprep3Dwelling  201  0.64  0.65  0.58   0.47 0.88 0.33
## T2Disprep3Furn      201  0.62  0.60  0.50   0.40 0.79 0.41
## T2Disprep3Famplan   201  0.71  0.65  0.57   0.48 0.62 0.49
## T2Disprep3Commplan  201  0.22  0.38  0.20   0.12 0.98 0.16
##
## Non missing response frequency for each item
##                        0    1 miss
## T2Disprep3Supplykit 0.73 0.27 0.01
## T2Disprep3Foodwater 0.22 0.78 0.01
## T2Disprep3Docs      0.04 0.96 0.01
## T2Disprep3Dwelling  0.12 0.88 0.01
```

```
## T2Disprep3Furn      0.21 0.79 0.01
## T2Disprep3Famplan   0.38 0.62 0.01
## T2Disprep3Commplan  0.02 0.98 0.01
```

```
psych::alpha(x = select(T3_DP_vars, -T3Disprep1futureEQrevCoded, -T3Disprep2monsoonprepfixedrev), cumula
```

```
##
## Reliability analysis
## Call: psych::alpha(x = select(T3_DP_vars, -T3Disprep1futureEQrevCoded,
##     -T3Disprep2monsoonprepfixedrev), cumulative = TRUE)
##
##   raw_alpha std.alpha G6(smc) average_r  S/N   ase mean  sd
##       0.49      0.47    0.47      0.11 0.88 0.048    6 1.2
##
##  lower alpha upper     95% confidence boundaries
## 0.4 0.49 0.58
##
##  Reliability if an item is dropped:
##                      raw_alpha std.alpha G6(smc) average_r  S/N alpha se
## T3Disprep3Supplykit      0.44      0.42    0.41     0.108 0.72    0.053
## T3Disprep3Foodwater      0.40      0.35    0.35     0.082 0.54    0.054
## T3Disprep3Docs           0.49      0.47    0.45     0.129 0.89    0.050
## T3Disprep3Dwelling       0.47      0.45    0.44     0.121 0.83    0.050
## T3Disprep3Furn           0.42      0.40    0.39     0.099 0.66    0.053
## T3Disprep3Famplan        0.39      0.39    0.38     0.096 0.63    0.057
## T3Disprep3Commplan       0.50      0.51    0.49     0.150 1.06    0.049
##
##  Item statistics
##                        n raw.r std.r r.cor r.drop mean    sd
## T3Disprep3Supplykit  202  0.68  0.51 0.364  0.289 0.52 0.501
## T3Disprep3Foodwater  202  0.59  0.62 0.550  0.338 0.88 0.330
## T3Disprep3Docs       202  0.23  0.41 0.219  0.145 0.99 0.099
## T3Disprep3Dwelling   202  0.36  0.45 0.263  0.195 0.97 0.183
## T3Disprep3Furn       202  0.55  0.55 0.424  0.303 0.89 0.312
## T3Disprep3Famplan    202  0.65  0.56 0.461  0.344 0.80 0.403
## T3Disprep3Commplan   202  0.15  0.32 0.061  0.043 0.99 0.121
##
## Non missing response frequency for each item
##                         0    1 miss
## T3Disprep3Supplykit  0.48 0.52    0
## T3Disprep3Foodwater  0.12 0.88    0
## T3Disprep3Docs       0.01 0.99    0
## T3Disprep3Dwelling   0.03 0.97    0
## T3Disprep3Furn       0.11 0.89    0
## T3Disprep3Famplan    0.20 0.80    0
## T3Disprep3Commplan   0.01 0.99    0
```

Having done that, we can ask whether disaster preparedness is correlated with our mental health measures (a primary assumption of the intervention).

```
cor.test( ~ disPrepBehaviorsT  + phqMean6_T, data = filtered, subset = timePoint == "1" )
```

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and phqMean6_T
```

```
## t = -1.7213, df = 200, p-value = 0.08674
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.25462744  0.01751965
## sample estimates:
##        cor
## -0.1208236
```

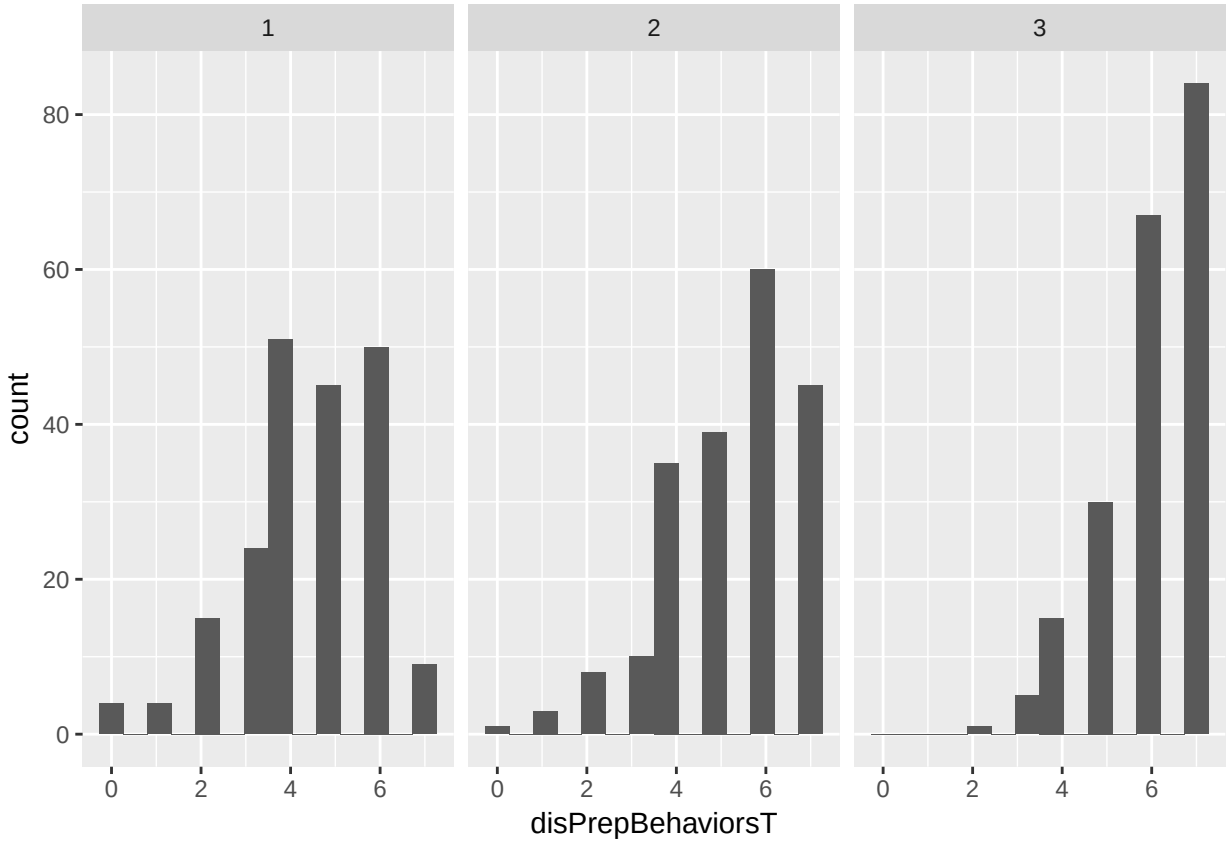
```
cor.test( ~ disPrepBehaviorsT  + ptsdMean11_T, data = filtered, subset = timePoint == "1" )
```

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and ptsdMean11_T
## t = -0.64879, df = 200, p-value = 0.5172
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.18272346  0.09280969
## sample estimates:
##         cor
## -0.04582849
```

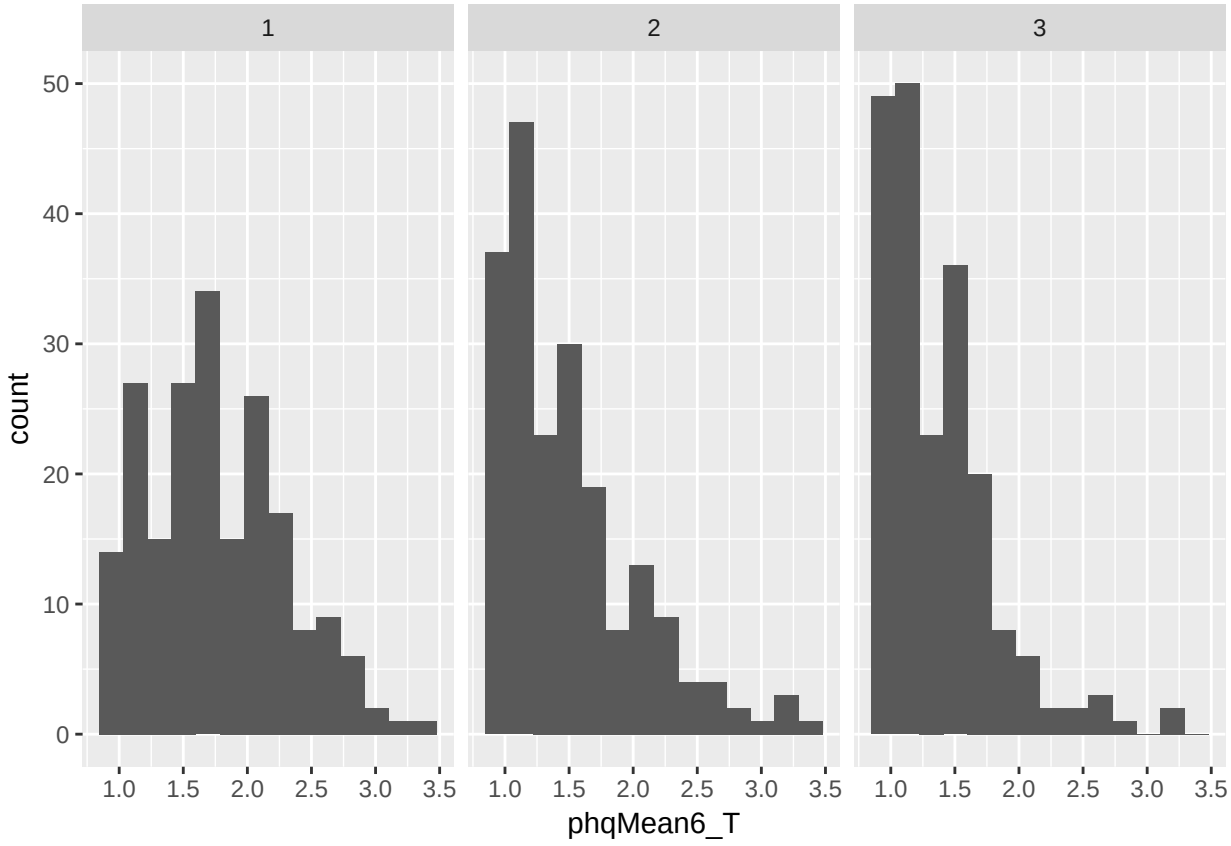
Next we take a look at histograms of key dependent measures faceted by time-point to see the shapes of their distributions. We plan to apply a linear model, so we need to understand to what degree that's appropriate and/or the most appropriate generalized linear model.

```
dvs = c('disPrepBehaviorsT', 'phqMean6_T', 'ptsdMean11_T', 'HelpSeekingMentalT', 'HelpSeekingDisT', 'so
var=dvs[1]
for(var in dvs) {
  print(ggplot(data = filtered, aes_string(x=var)) + geom_histogram(bins=14) + facet_grid(.~timePoint))
}
```

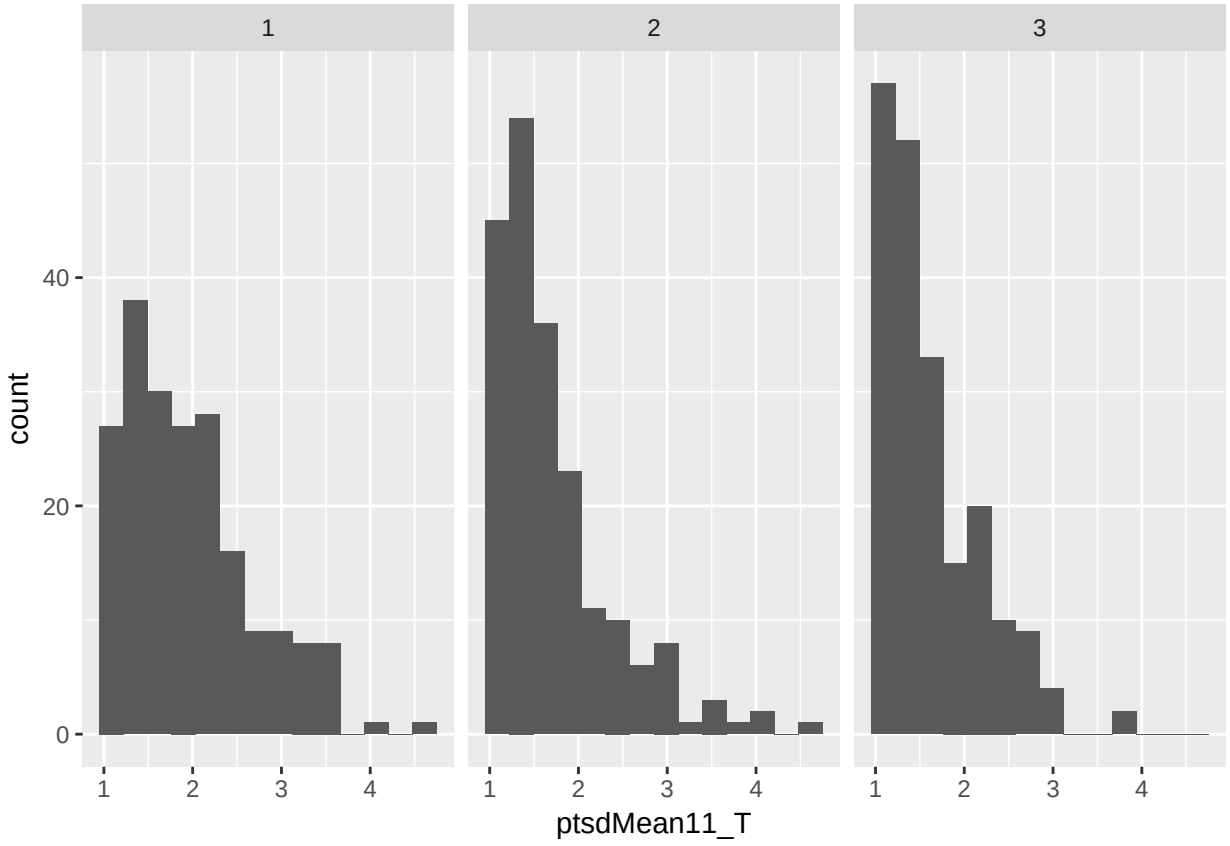
```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



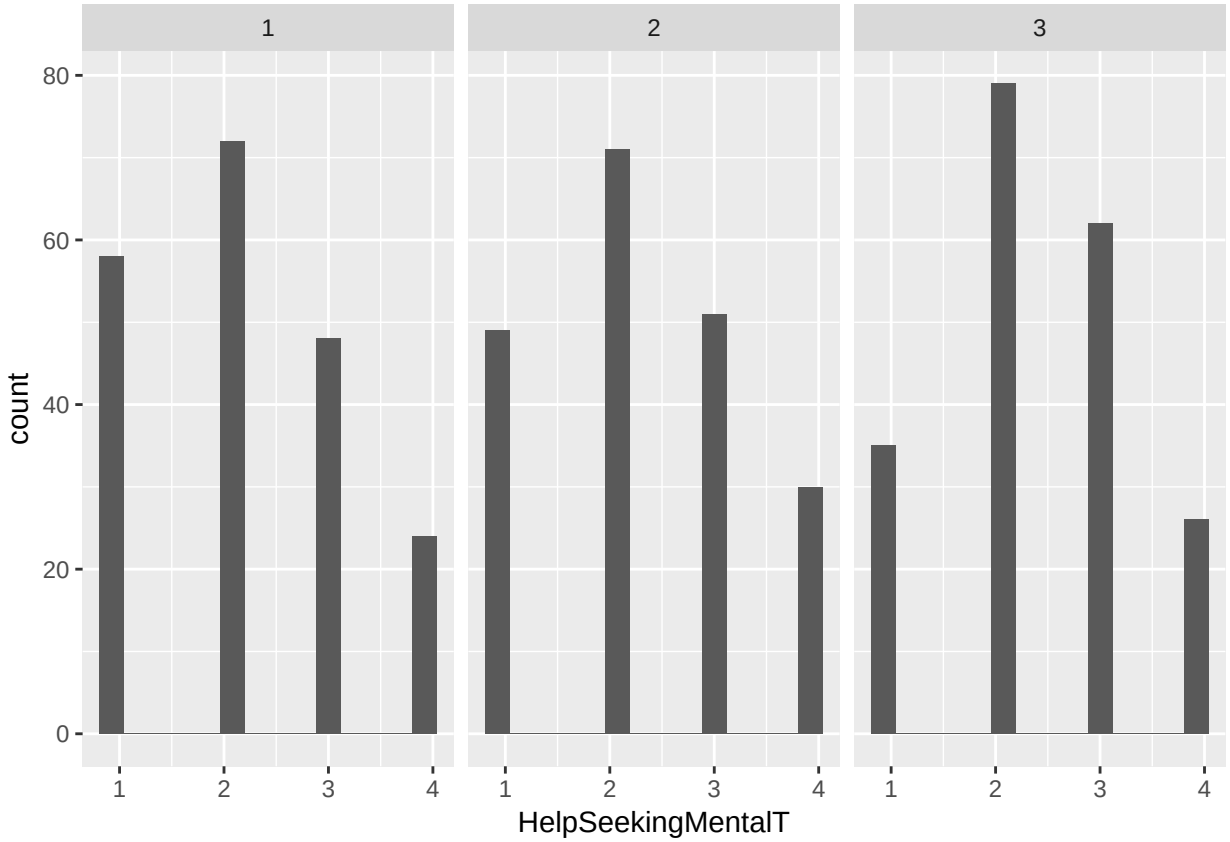

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



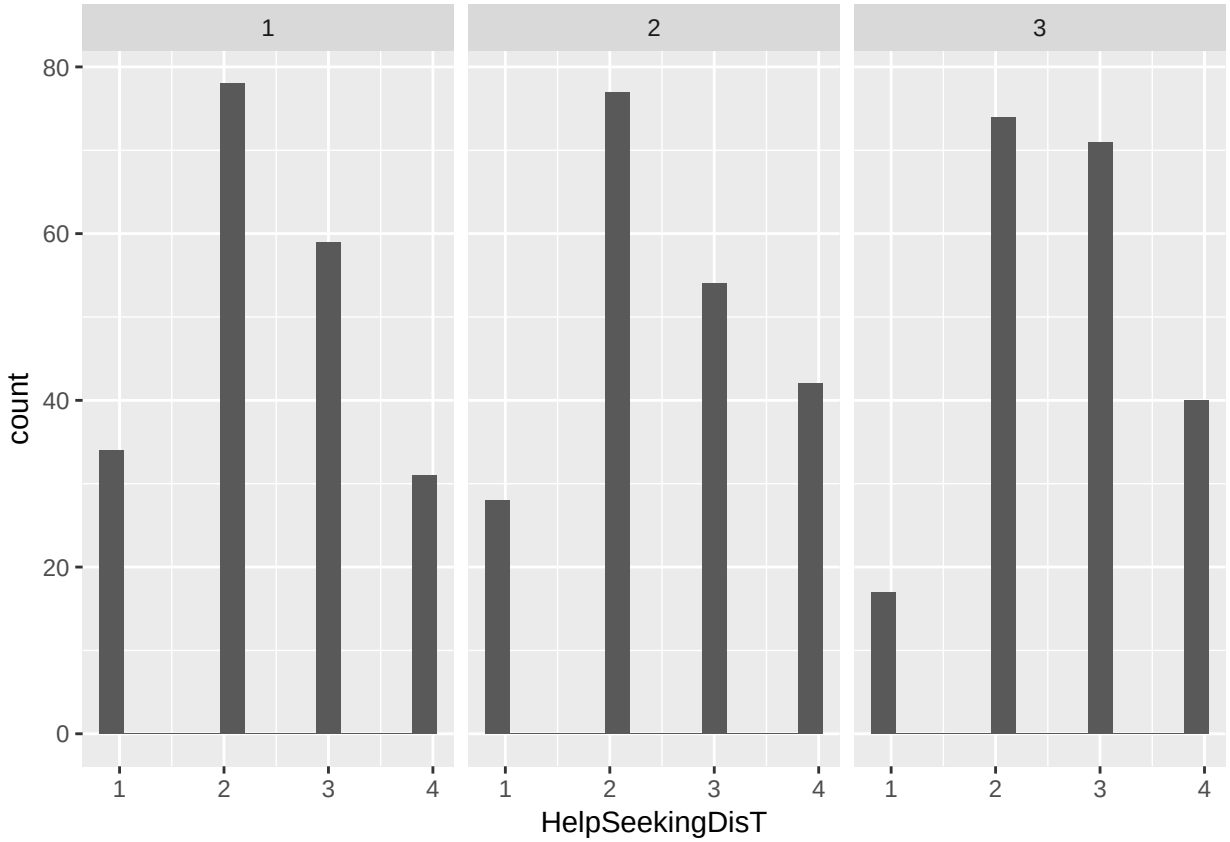

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



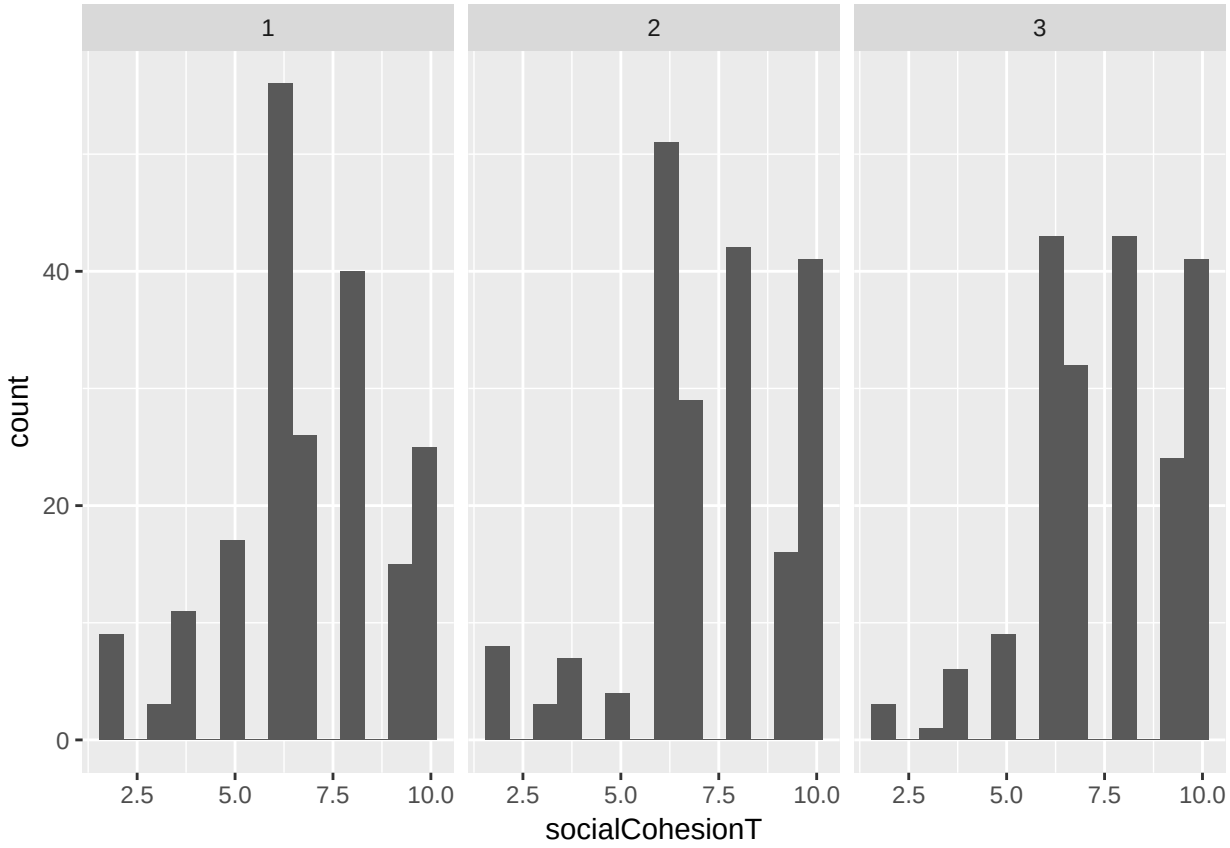

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```




```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```




```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```




```
factor_dvs <- c('HelpSeekingMentalT', 'HelpSeekingDisT')
filtered %<>% mutate_at(factor_dvs, funs(factor(.)))
```

It appears the first depedent measure follows a binomial process, the second two may be approximated by a gamma process, but they contain zeros; and the remaining may be reasonably approximated by a Gaussian distribution. The last might also be considered binomial.

Function for plotting

Containing data organized by city across time points and marginal means for intervention effect

```
plot_line_bar <- function(dv, limits, mmeans, theme_style = theme_grey(), title = "", position=c(.8825,

  if(logit) {
    mmeans_summary <- summary(mmeans, type="response")*logit
  } else {
    mmeans_summary <- summary(mmeans)
  }


  results <- data.frame(interventPlotting = factor(c(1,2), labels=c('Pre-intervention', 'Post-interventi
                        SE = mmeans_summary[,'SE'], calc_margins = mmeans_summary[,2])
  results$plus <- results$calc_margins + results$SE
  results$minus <- results$calc_margins - results$SE
```

```
  if(is.factor(filtered[[dv]])) {
    filtered[[paste0(dv, '_numeric')]] <- as.numeric(filtered[[dv]])
    dv <- paste0(dv, '_numeric')
  }

  breaks <- seq(limits[1], limits[2], by=by)
  wrap_113 <- wrap_format(113)

  line <- ggplot(filtered, aes_string(x="timePoint", y=dv, group="city", shape="city")) +
        geom_hline(yintercept = results$calc_margins[1], color = "#F8766D", alpha = .75, linetype = 3) +
        geom_hline(yintercept = results$calc_margins[2], color = "#00BFC4", alpha = .5, linetype = 1) +
        stat_summary(geom="errorbar", fun.data=mean_se, fun.args=list(mult=1), width=.09, size=1, alpha=
        stat_summary(data=subset(filtered, interventPlotting == 'Intervention'), aes(color=interventPlo
        stat_summary(data=subset(filtered, interventionT == 'Control'), aes(color=interventionT), geom=
        stat_summary(geom="point", fun.y="mean", size=4, aes(color=interventionT))  +
        annotate("rect", xmin = 0, xmax = Inf, ymin=min(results$calc_margins), ymax=max(results$calc_ma
        coord_cartesian(ylim=limits) +
        scale_shape_discrete("") +
        scale_color_discrete("",labels=c('Pre-intervention', 'Intervention')) +
        labs(color="Condition", shape="City", x="Time point", y=title, caption = wrap_113(sprintf(capti
        theme_style +
        theme(
            legend.position=position,
            plot.caption=element_text(hjust=0),
            legend.box.just="left",
            legend.background = element_rect(color = "transparent", fill = "transparent"),
            legend.key = element_rect(color = "transparent", fill = "transparent"),
            legend.title = element_blank()
        )   + guides(shape = guide_legend(override.aes = list(shape=c(19,17))),
              colour = guide_legend(override.aes = list(linetype = c(3,1), shape=NA)))
  line
  if(save) {
    ggsave(paste0(title, '.pdf'), device=cairo_pdf, width = 7.5, height = 5)
  }
  print(line)
}
```

Performing the tests of pre-planned hypotheses of intervention effects using linear mixed models

Subjects' data were collected across three time points, and subjects were clustered within communities (2), resulting in a three-level hierarchical model (measurements clustered within subjects clustered within community) with fixed effects of time point and intervention and random intercepts at the community and subject level. First we define a model using `glmer` or `lmer` from the `lme4` package; `afex::mixed` gives us ANOVA Type 3 p-values for the fixed effects by Kenward-Roger method. Alternatively, `glmmTMB` gives us fixed effects p-values directly within the model. We use the `lsmeans` package to compute marginal means. `car::Anova` will be used to generate type III ANOVA-style contrasts of factor effects. We'll also calculate separate models with `city` as a factor (instead of `interventionT`) in order to generate contrasts for subsequent labeling of significance of our plots. Exploration of these results indicated the random effect of `city` was close to zero, so it was removed from the model, as per testing by restricted likelihood ratio test via the `RLRsim` package (for some dependent variables, this is true of the main `interventionT` model, as well). `lsmeans` computes an 'exact' Tukey adjustment based on a multivariate t-distribution via a Monte

Carlo method for our contrasts of marginal means from the time point * city model.

```
filtered$disPrepSize <- 7 # 7 binary questions summed to make this scale
#disPrep <- glmmTMB(disPrepBehaviorsT/disPrepSize ~ timePoint * gender + interventionT * gender + (1|ci
disPrep <- glmer(cbind(disPrepBehaviorsT, disPrepSize-disPrepBehaviorsT) ~ timePoint * gender + interve
disPrepLinear <- lmer(disPrepBehaviorsT ~ timePoint * gender + interventionT * gender + (1|city/ID), da

# here because we use a binomial family model, we cannot use RLRsim to test the random effects; however
summary(disPrep)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT) ~ timePoint *
##     gender + interventionT * gender + (1 | city/ID)
##    Data: filtered
##
##      AIC      BIC   logLik deviance df.resid
##   1824.0   1867.9   -902.0   1804.0      590
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.6915 -0.5037  0.1184  0.7639  2.4356
##
## Random effects:
##  Groups  Name        Variance Std.Dev.
##  ID:city (Intercept) 0.40022  0.6326
##  city    (Intercept) 0.07377  0.2716
## Number of obs: 600, groups:  ID:city, 201; city, 2
##
## Fixed effects:
##                                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          0.65006    0.21293   3.053  0.00227
## timePoint2                           0.27344    0.13604   2.010  0.04442
## timePoint3                           0.61616    0.24178   2.548  0.01082
## genderMale                          -0.09009    0.15245  -0.591  0.55455
## interventionTIntervention            0.77878    0.20448   3.809  0.00014
## timePoint2:genderMale                0.23023    0.21612   1.065  0.28673
## timePoint3:genderMale                0.30813    0.37691   0.818  0.41363
## genderMale:interventionTIntervention -0.33342    0.31480  -1.059  0.28953
##
## (Intercept)                          **
## timePoint2                           *
## timePoint3                           *
## genderMale
## interventionTIntervention            ***
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
```

```
## timePoint2  -0.173
## timePoint3  -0.092  0.663
## genderMale  -0.259  0.256  0.147
## intrvntnTIn -0.009 -0.580 -0.858 -0.006
## tmPnt2:gndM  0.112 -0.594 -0.372 -0.432  0.316
## tmPnt3:gndM  0.062 -0.376 -0.579 -0.243  0.481  0.636
## gndrMl:ntTI  0.003  0.323  0.488 -0.008 -0.571 -0.541 -0.843
```

```
Anova(disPrep, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT)
##                        Chisq Df Pr(>Chisq)
## (Intercept)           9.3203  1  0.0022663 **
## timePoint             6.6785  2  0.0354642 *
## gender                0.3492  1  0.5545454
## interventionT        14.5051  1  0.0001398 ***
## timePoint:gender      1.1680  2  0.5576759
## gender:interventionT  1.1218  1  0.2895304
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#confint(disPrepModel) #gets us the confidence intervals

disPrepCity <- glmer(cbind(disPrepBehaviorsT, disPrepSize-disPrepBehaviorsT) ~ timePoint * city + (1|ID)
Anova(disPrepCity, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT)
##                  Chisq Df Pr(>Chisq)
## (Intercept)     62.924  1  2.148e-15 ***
## timePoint      122.555  2  < 2.2e-16 ***
## city            10.122  1  0.0014652 **
## timePoint:city  17.877  2  0.0001313 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
disPrepCityMM <- lsmeans::lsmeans(disPrepCity, ~ timePoint * city)
summary(rbind(pairs(disPrepCityMM, by="city")[c(1,3,4,6)], pairs(disPrepCityMM, by="timePoint")))
```

```
##  timePoint contrast           city       estimate        SE df z.ratio
##  .         1 - 2              Chhaling -1.0740170 0.1402619 NA  -7.657
##  .         2 - 3              Chhaling -0.5439336 0.1740732 NA  -3.125
##  .         1 - 2              Tathali  -0.3168444 0.1131159 NA  -2.801
##  .         2 - 3              Tathali  -0.9026863 0.1272260 NA  -7.095
##  1         Chhaling - Tathali .         0.4649701 0.1461490 NA   3.181
##  2         Chhaling - Tathali .         1.2221427 0.1646383 NA   7.423
##  3         Chhaling - Tathali .         0.8633900 0.1896992 NA   4.551
##  p.value
##   <.0001
##   0.0125
##   0.0357
##   <.0001
##   0.0103
```

```
##   <.0001
##   <.0001
##
## Results are given on the log odds ratio (not the response) scale.
## P value adjustment: bonferroni method for 7 tests
```

Use plotting function to generate plots

Have to pre-determine y-axis limits to equate them between panels. Pass marginal means of intervention effect to function.

```
#mmeans <- lsmeans::lsmeans(disPrep, ~interventionT)  #marginal means
mmeans <- lsmeans::lsmeans(disPrepLinear, ~interventionT)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
summary(mmeans)
```

```
##  interventionT   lsmean        SE   df lower.CL upper.CL
##  Control       4.897719 0.3395881 1.16 1.782576 8.012862
##  Intervention  5.598916 0.3396929 1.17 2.482812 8.715020
##
## Results are averaged over the levels of: timePoint, gender
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```
limits <- c(4,6.5)
theme <- theme_minimal()
rnge <- range(filtered$disPrepBehaviorsT, na.rm = TRUE)
caption = "Seven-item yes/no scale (range %d - %d), with greater values indicating greater engagement i
#plot_line_bar("disPrepBehaviorsT", limits, mmeans, theme, "Disaster Preparation Behaviors", logit=7, r
plot_line_bar("disPrepBehaviorsT", limits, mmeans, theme, "Disaster Preparation Behaviors", logit=FALSE
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

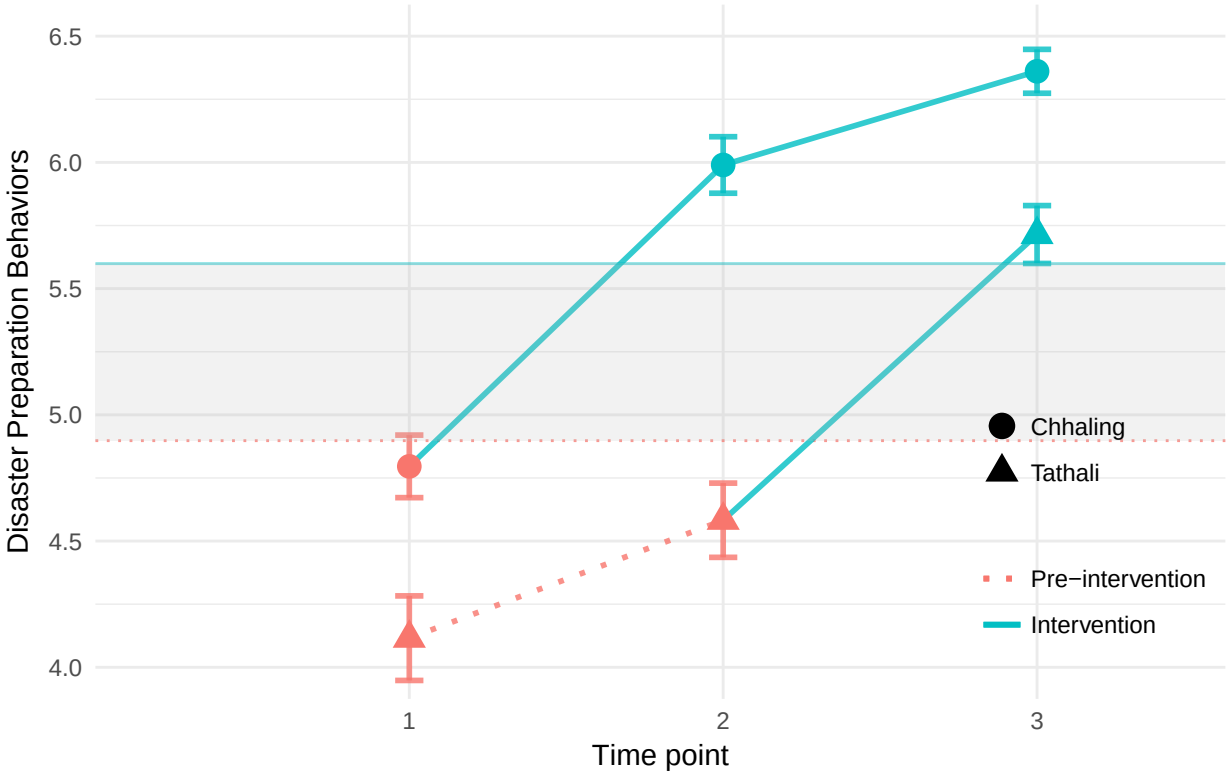
```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

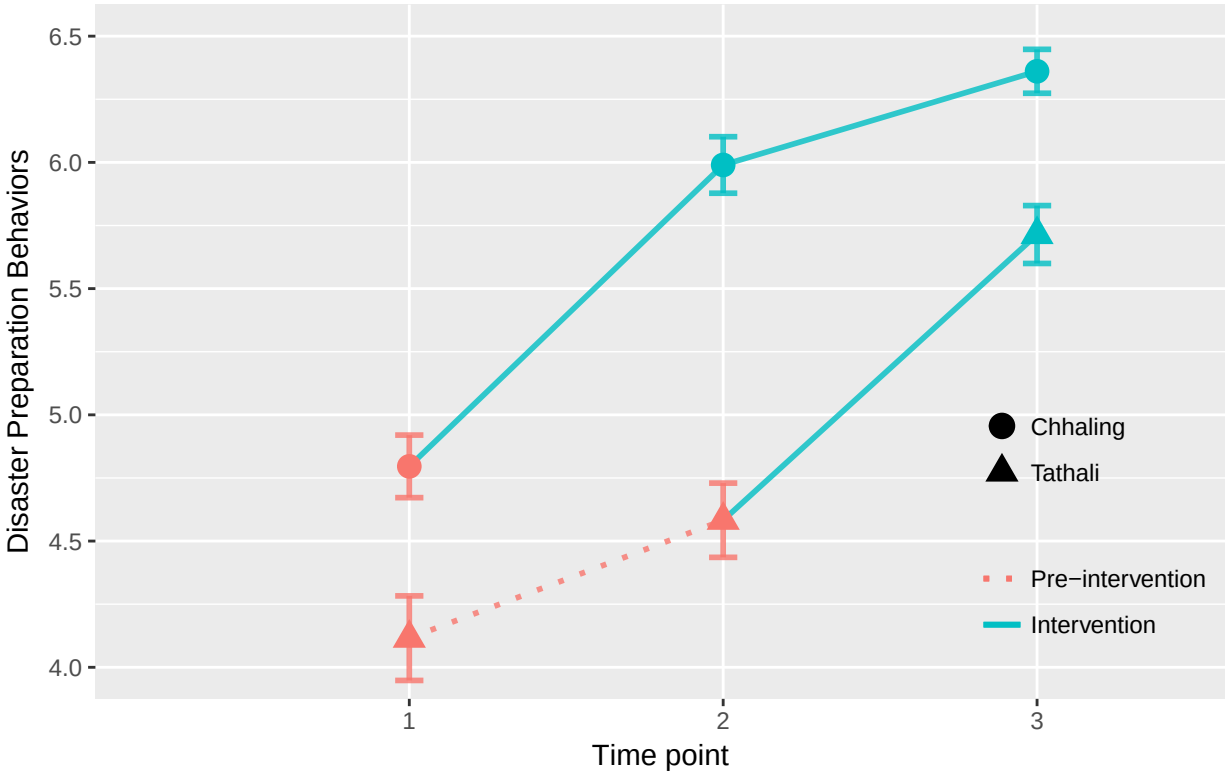


Seven−item yes/no scale (range 0 − 7), with greater values indicating greater engagement in disa behaviors. Shaded region depicts size of difference between pre− and post−intervention marginal

Another plot of the same data, passing a different ggtheme.

```
theme <- theme_grey()
plot_line_bar("disPrepBehaviorsT", limits, mmeans, theme, "Disaster Preparation Behaviors", logit=7, ca
```

```
## Warning in Ops.factor(left, right): '*' not meaningful for factors
## Warning: Removed 4 rows containing non-finite values (stat_summary).
## Warning: Removed 2 rows containing non-finite values (stat_summary).
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```



Seven−item yes/no scale (range 0 − 7), with greater values indicating greater engagement in disa behaviors. Shaded region depicts size of difference between pre− and post−intervention marginal

We continue this style of analysis for the other dependent measures of interest: PTSD, PHQ, help-seeking (mental health related), help-seeking (disaster related), and social cohesion.

```
mA <- lmer(phqMean6_T ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- lmer(phqMean6_T ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
m <- lmer(phqMean6_T ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
exactRLRT(m=m, mA=mA, m0=m0)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 0.011137, p-value = 0.2813
```

```
# results tell us city random effect is not needed, save m0 model
phq <- m0

summary(phq)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
## Formula: phqMean6_T ~ timePoint * gender + interventionT * gender + (1 |
##     ID)
##    Data: filtered
##
## REML criterion at convergence: 698.4
```

```
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8096 -0.5518 -0.0502  0.4477  3.4024
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.1090   0.3302
##  Residual             0.1146   0.3385
## Number of obs: 600, groups:  ID, 201
##
## Fixed effects:
##                                     Estimate Std. Error        df
## (Intercept)                          1.81686    0.04163 402.90000
## timePoint2                          -0.12623    0.05489 431.20000
## timePoint3                          -0.15563    0.08106 461.10000
## genderMale                          -0.13766    0.06956 402.90000
## interventionTIntervention           -0.26847    0.06923 486.00000
## timePoint2:genderMale               -0.02173    0.08937 428.60000
## timePoint3:genderMale                0.06311    0.13548 462.60000
## genderMale:interventionTIntervention  0.01850    0.11542 486.80000
##                                     t value Pr(>|t|)
## (Intercept)                          43.638  < 2e-16 ***
## timePoint2                           -2.300  0.02193 *
## timePoint3                           -1.920  0.05548 .
## genderMale                           -1.979  0.04852 *
## interventionTIntervention            -3.878  0.00012 ***
## timePoint2:genderMale                -0.243  0.80798
## timePoint3:genderMale                 0.466  0.64153
## genderMale:interventionTIntervention  0.160  0.87271
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
## timePoint2  -0.389
## timePoint3  -0.263  0.743
## genderMale  -0.599  0.233  0.158
## intrvntnTIn  0.000 -0.636 -0.854  0.000
## tmPnt2:gndM  0.239 -0.614 -0.456 -0.399  0.390
## tmPnt3:gndM  0.158 -0.444 -0.598 -0.263  0.511  0.728
## gndrMl:ntTI  0.000  0.381  0.512  0.000 -0.600 -0.613 -0.853
```

```
Anova(phq, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: phqMean6_T
##                          Chisq Df Pr(>Chisq)
## (Intercept)          1904.3002  1  < 2.2e-16 ***
## timePoint               5.3896  2  0.0675542 .
## gender                  3.9157  1  0.0478359 *
## interventionT          15.0376  1  0.0001054 ***
## timePoint:gender        0.9383  2  0.6255196
## gender:interventionT    0.0257  1  0.8726482
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
mmeans <- lsmeans::lsmeans(phq, ~interventionT)  #marginal means
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
summary(mmeans)
```

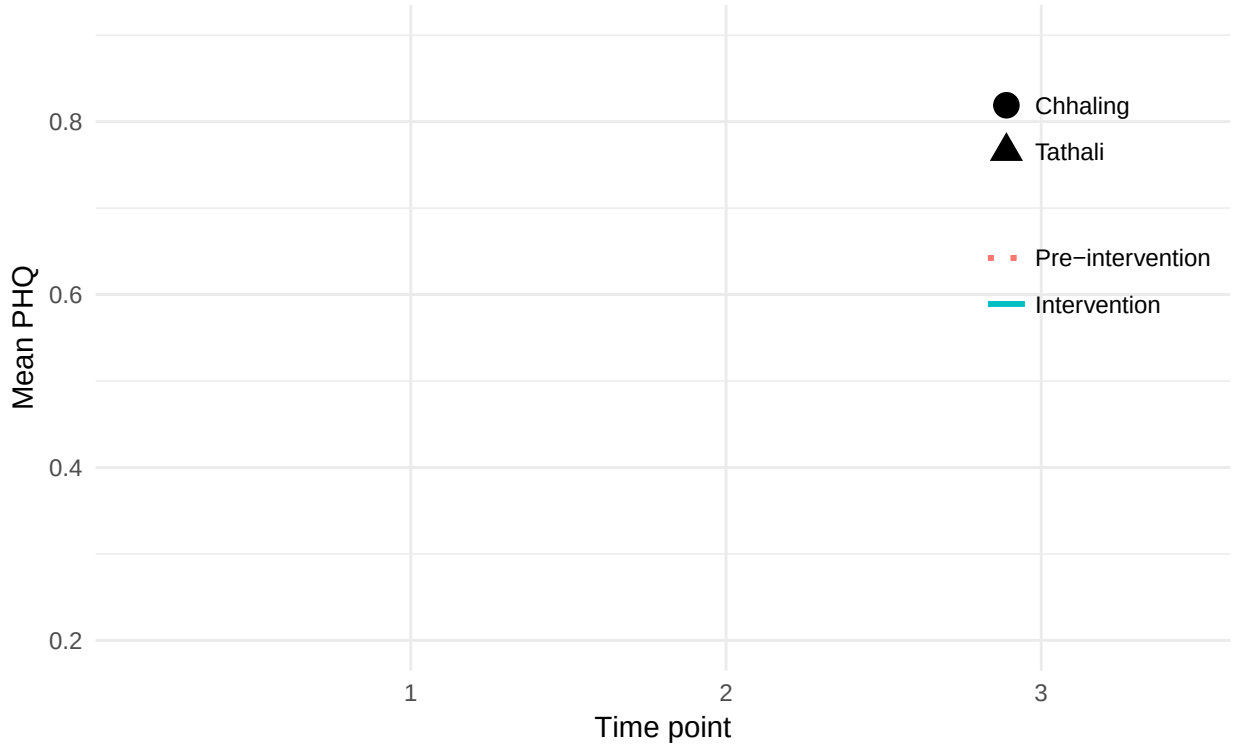
```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       1.660976 0.04005550 486.18 1.582273 1.739679
##  Intervention  1.401757 0.04070588 497.82 1.321775 1.481738
##
## Results are averaged over the levels of: timePoint, gender
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```
limits <- c(.2,.9)
theme <- theme_minimal()
#rnge <- range(filtered$phqMean6_T, na.rm = TRUE)'
rnge <- c(0,3)
caption = "Mean of nine-item Patient Health Questionnaire (PHQ, items each range %d - %d), with greater
plot_line_bar("phqMean6_T", limits, mmeans, theme, "Mean PHQ", position=c(.8825, .70), by = .2, caption
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```



Mean of nine−item Patient Health Questionnaire (PHQ, items each range 0 − 3), with greater valu
greater depressive symptoms. Shaded region depicts size of difference between pre− and post−in
marginal means.

```
phqCity <- lmer(phqMean6_T ~ timePoint * city + (1|ID), data=filtered)
Anova(phqCity, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: phqMean6_T
##                    Chisq Df Pr(>Chisq)
## (Intercept)    1340.6310  1  < 2.2e-16 ***
## timePoint        76.3819  2  < 2.2e-16 ***
## city              0.0305  1     0.8614
## timePoint:city   23.4876  2  7.938e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
phqCityMM <- lsmeans::lsmeans(phqCity, ~ timePoint * city)
summary(rbind(pairs(phqCityMM, by="city")[c(1,3,4,6)], pairs(phqCityMM, by="timePoint")))
```

```
##  timePoint contrast           city        estimate         SE     df
##  .         1 - 2              Chhaling  0.38449546 0.04858245 396.39
##  .         2 - 3              Chhaling -0.03554410 0.04874916 397.00
##  .         1 - 2              Tathali   0.15091491 0.04738920 398.12
##  .         2 - 3              Tathali   0.28200171 0.04723800 397.53
##  1         Chhaling - Tathali .         0.01182073 0.06770714 399.75
##  2         Chhaling - Tathali .        -0.22175983 0.06781340 401.14
##  3         Chhaling - Tathali .         0.09578598 0.06772266 399.95
##  t.ratio p.value
##    7.914  <.0001
##   -0.729  1.0000
##    3.185  0.0109
##    5.970  <.0001
##    0.175  1.0000
##   -3.270  0.0082
##    1.414  1.0000
##
## P value adjustment: bonferroni method for 7 tests
```

```
mA <- lmer(ptsdMean11_T ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- lmer(ptsdMean11_T ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
m <- lmer(ptsdMean11_T ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
exactRLRT(m=m, mA=mA, m0=m0)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 0.20278, p-value = 0.1835
```

```
#results tell us city random effect not needed, keep m0
ptsd <- m0

summary(ptsd)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
```

```
## Formula: ptsdMean11_T ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
##    Data: filtered
##
## REML criterion at convergence: 944.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8156 -0.5534 -0.0748  0.4383  4.0976
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.2353   0.4851
##  Residual             0.1531   0.3913
## Number of obs: 600, groups:  ID, 201
##
## Fixed effects:
##                                     Estimate Std. Error        df
## (Intercept)                          2.06541    0.05487 343.00000
## timePoint2                          -0.12169    0.06392 420.50000
## timePoint3                          -0.10603    0.09495 441.60000
## genderMale                          -0.30172    0.09168 343.00000
## interventionTIntervention           -0.27533    0.08149 459.20000
## timePoint2:genderMale               -0.01944    0.10403 418.70000
## timePoint3:genderMale                0.04476    0.15874 442.80000
## genderMale:interventionTIntervention  0.02576    0.13588 459.90000
##                                     t value Pr(>|t|)
## (Intercept)                          37.641  < 2e-16 ***
## timePoint2                           -1.904 0.057620 .
## timePoint3                           -1.117 0.264710
## genderMale                           -3.291 0.001102 **
## interventionTIntervention            -3.379 0.000791 ***
## timePoint2:genderMale                -0.187 0.851833
## timePoint3:genderMale                 0.282 0.778108
## genderMale:interventionTIntervention  0.190 0.849710
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
## timePoint2  -0.338
## timePoint3  -0.228  0.747
## genderMale  -0.599  0.203  0.136
## intrvntnTIn  0.000 -0.642 -0.858  0.000
## tmPnt2:gndM  0.208 -0.614 -0.459 -0.347  0.395
## tmPnt3:gndM  0.136 -0.447 -0.598 -0.228  0.513  0.732
## gndrMl:ntTI  0.000  0.385  0.515  0.000 -0.600 -0.620 -0.858
```

```
Anova(ptsd, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: ptsdMean11_T
##                            Chisq Df Pr(>Chisq)
## (Intercept)           1416.8809  1  < 2.2e-16 ***
```

```
## timePoint               3.8354  2  0.1469443
## gender                 10.8311  1  0.0009981 ***
## interventionT          11.4144  1  0.0007288 ***
## timePoint:gender        0.4133  2  0.8133063
## gender:interventionT    0.0359  1  0.8496268
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
mmeans <- lsmeans::lsmeans(ptsd, ~interventionT)  #marginal means
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
summary(mmeans)
```

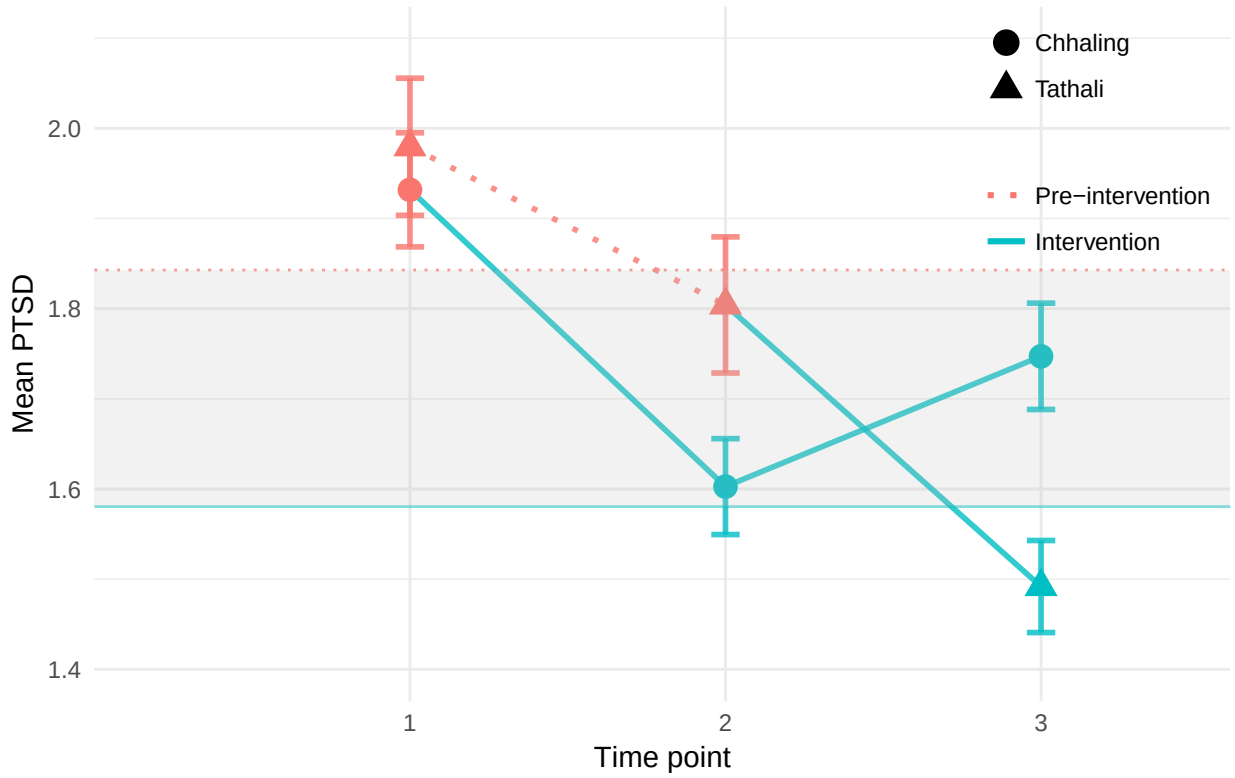
```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       1.842859 0.05166687 437.78 1.741313 1.944405
##  Intervention  1.580415 0.05235975 449.68 1.477507 1.683322
##
## Results are averaged over the levels of: timePoint, gender
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```
limits <- c(1.4, 2.1)
theme <- theme_minimal()
#rnge <- range(filtered$ptsdMean11_T, na.rm = TRUE)
rnge = c(1,5)
caption = "Mean of 17-item scale (items each range %d - %d), with greater values indicating greater exp
plot_line_bar("ptsdMean11_T", limits, mmeans, theme, "Mean PTSD", position=c(.8825, .805), by=.2, capti
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```



Mean of 17−item scale (items each range 1 − 5), with greater values indicating greater expression symptoms. Shaded region depicts size of difference between pre− and post−intervention marginal

```
ptsdCity <- lmer(ptsdMean11_T ~ timePoint * city + (1|ID), data=filtered)
Anova(ptsdCity, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: ptsdMean11_T
##                   Chisq Df Pr(>Chisq)
## (Intercept)    873.9313  1  < 2.2e-16 ***
## timePoint       36.6766  2  1.086e-08 ***
## city             0.5091  1     0.4755
## timePoint:city  36.9663  2  9.394e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
ptsdCityMM <- lsmeans::lsmeans(ptsdCity, ~ timePoint * city)
summary(rbind(pairs(ptsdCityMM, by="city")[c(1,3,4,6)], pairs(ptsdCityMM, by="timePoint")))
```

```
##  timePoint contrast           city       estimate         SE     df
##  .         1 - 2              Chhaling  0.3291567 0.05456811 396.15
##  .         2 - 3              Chhaling -0.1389565 0.05476388 396.55
##  .         1 - 2              Tathali   0.1918248 0.05325139 397.29
##  .         2 - 3              Tathali   0.3130690 0.05307347 396.90
##  1         Chhaling - Tathali .        -0.0649028 0.09096324 324.35
##  2         Chhaling - Tathali .        -0.2022347 0.09106758 325.45
##  3         Chhaling - Tathali .         0.2497908 0.09097847 324.51
##  t.ratio p.value
##    6.032  <.0001
```

```
##   -2.537  0.0809
##    3.602  0.0025
##    5.899  <.0001
##   -0.714  1.0000
##   -2.221  0.1894
##    2.746  0.0446
##
## P value adjustment: bonferroni method for 7 tests
```

```
#mA <- lmer(HelpSeekingMentalT ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filter
#m0 <- lmer(HelpSeekingMentalT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- lmer(HelpSeekingMentalT ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# results tell us city random effect not needed, keep m0
help_mental <- clmm(HelpSeekingMentalT ~ timePoint * gender + interventionT * gender + (1|ID), data=fil
help_mental_linear <- lmer(as.numeric(HelpSeekingMentalT) ~ timePoint * gender + interventionT * gender
summary(help_mental)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula:
## HelpSeekingMentalT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  600  -763.69 1549.37 824(2475) 7.85e-04 2.1e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 1.472    1.213
## Number of groups:  ID 201
##
## Coefficients:
##                                     Estimate Std. Error z value Pr(>|z|)
## timePoint2                           -0.3318     0.3094  -1.072   0.2835
## timePoint3                           -0.4584     0.4407  -1.040   0.2983
## genderMale                            0.2633     0.3385   0.778   0.4367
## interventionTIntervention             0.8459     0.3767   2.246   0.0247
## timePoint2:genderMale                 0.6762     0.5124   1.320   0.1870
## timePoint3:genderMale                 0.6045     0.7465   0.810   0.4181
## genderMale:interventionTIntervention -0.3054     0.6278  -0.486   0.6266
##
## timePoint2
## timePoint3
## genderMale
## interventionTIntervention           *
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
```

```
## 1|2  -1.2103     0.2153  -5.622
## 2|3   0.8891     0.2108   4.218
## 3|4   2.7911     0.2514  11.103
## (9 observations deleted due to missingness)
```

```
Anova(help_mental, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingMentalT
##                       LR Chisq Df Pr(>Chisq)
## timePoint             0.00000  2     1.0000
## gender                0.00000  1     1.0000
## interventionT         0.00000  1     1.0000
## timePoint:gender      1.80204  2     0.4062
## gender:interventionT  0.23678  1     0.6265
```

```
mmeans <- lsmeans::lsmeans(help_mental_linear, ~interventionT)  #marginal means
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
summary(mmeans)
```

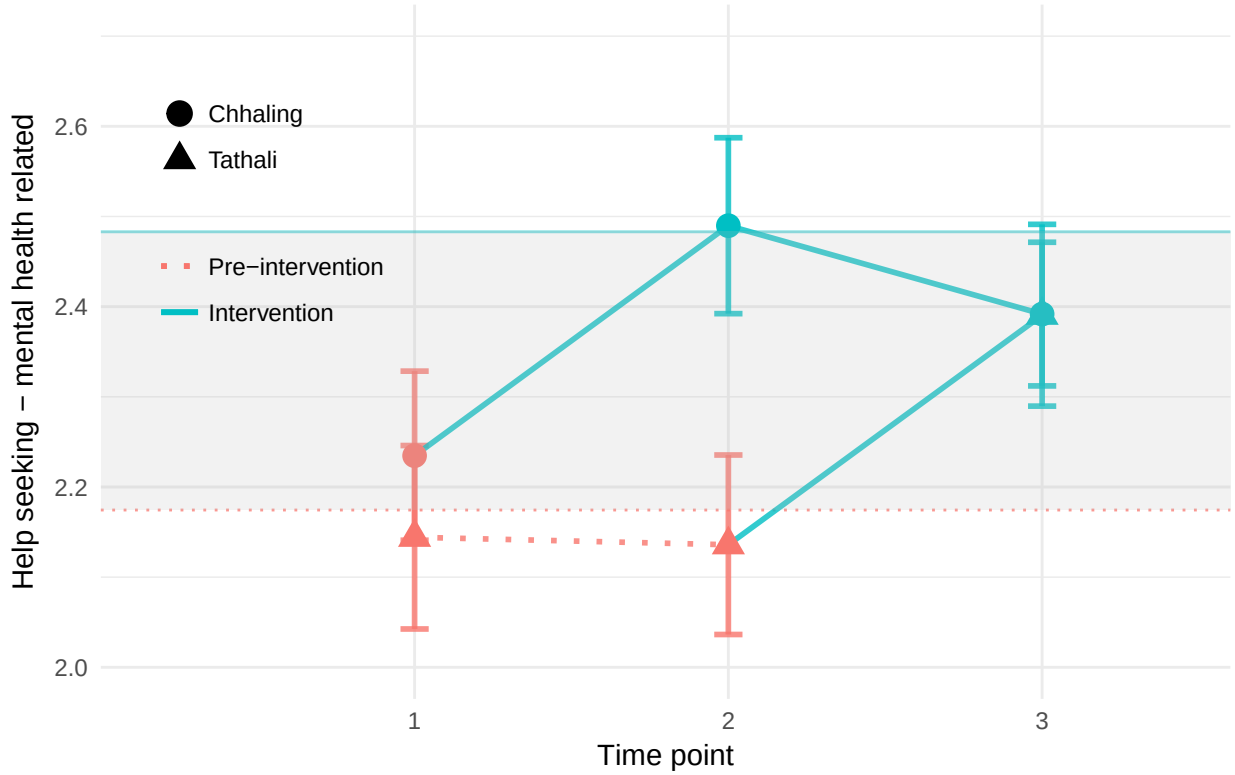
```
##  interventionT   lsmean        SE     df lower.CL upper.CL
##  Control       2.174446 0.0827127 530.33 2.011962 2.336931
##  Intervention  2.483021 0.0844035 539.69 2.317215 2.648827
##
## Results are averaged over the levels of: timePoint, gender
## Degrees-of-freedom method: satterthwaite
## Results are given on the as.numeric (not the response) scale.
## Confidence level used: 0.95
```

```
limits <- c(2, 2.7)
theme <- theme_minimal()
rnge <- range(as.numeric(filtered$HelpSeekingMentalT), na.rm = TRUE)
caption = "Greater values indicate greater willingness to seek help from others for mental health conce
plot_line_bar("HelpSeekingMentalT", limits, mmeans, theme, "Help seeking - mental health related", posi
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```



Greater values indicate greater willingness to seek help from others for mental health concerns (s
range 1 − 4). Shaded region depicts size of difference between pre− and post−intervention margi

```
help_mentalCity <- clmm(HelpSeekingMentalT ~ timePoint * city + (1|ID), data=filtered)
Anova(help_mentalCity, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingMentalT
##                LR Chisq Df Pr(>Chisq)
## timePoint        0.0000  2    1.00000
## city             0.0000  1    0.99982
## timePoint:city   4.8739  2    0.08743 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
help_mentalCityMM <- lsmeans::lsmeans(help_mentalCity, ~ timePoint * city)
summary(rbind(pairs(help_mentalCityMM, by="city")[c(1,3,4,6)], pairs(help_mentalCityMM, by="timePoint")))
```

```
##  timePoint contrast           city        estimate        SE df z.ratio
##  .         1 - 2              Chhaling -0.56329742 0.2692592 NA  -2.092
##  .         2 - 3              Chhaling  0.20530900 0.2634309 NA   0.779
##  .         1 - 2              Tathali  -0.02407587 0.2742125 NA  -0.088
##  .         2 - 3              Tathali  -0.61985800 0.2725444 NA  -2.274
##  1         Chhaling - Tathali .         0.28465921 0.3242577 NA   0.878
##  2         Chhaling - Tathali .         0.82388076 0.3245662 NA   2.538
##  3         Chhaling - Tathali .        -0.00128625 0.3163447 NA  -0.004
##  p.value
##   0.2551
##   1.0000
```

```
##   1.0000
##   0.1606
##   1.0000
##   0.0780
##   1.0000
##
## P value adjustment: bonferroni method for 7 tests
```

```
#mA <- clmm(HelpSeekingDisT ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- clmm(HelpSeekingDisT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(HelpSeekingDisT ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is indeed needed; we'll take mA
help_dist <- m0
help_dist_linear <- lmer(as.numeric(HelpSeekingDisT) ~ timePoint * gender + interventionT * gender + (1
summary(help_dist)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: HelpSeekingDisT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  600  -737.98 1497.97 865(2598) 5.06e-04 1.9e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 1.613    1.27
## Number of groups:  ID 201
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## timePoint2                          -0.5330     0.3151  -1.691  0.09076
## timePoint3                          -0.7234     0.4494  -1.610  0.10747
## genderMale                           0.6945     0.3420   2.031  0.04229
## interventionTIntervention            1.1143     0.3844   2.899  0.00374
## timePoint2:genderMale                1.3823     0.5276   2.620  0.00879
## timePoint3:genderMale                1.8614     0.7567   2.460  0.01390
## genderMale:interventionTIntervention -1.3588     0.6399  -2.123  0.03372
##
## timePoint2                          .
## timePoint3
## genderMale                          *
## interventionTIntervention           **
## timePoint2:genderMale               **
## timePoint3:genderMale               *
## genderMale:interventionTIntervention *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2  -1.9957     0.2382  -8.378
## 2|3   0.5851     0.2147   2.726
```

```
## 3|4   2.5743     0.2495  10.320
## (9 observations deleted due to missingness)
```

```
Anova(help_dist, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingDisT
##                       LR Chisq Df Pr(>Chisq)
## timePoint               0.0000  2    1.00000
## gender                  0.0000  1    1.00000
## interventionT           0.0000  1    1.00000
## timePoint:gender        7.5204  2    0.02328 *
## gender:interventionT    4.5235  1    0.03343 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
mmeans <- lsmeans::lsmeans(help_dist_linear, ~interventionT)  #marginal means
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
summary(mmeans)
```

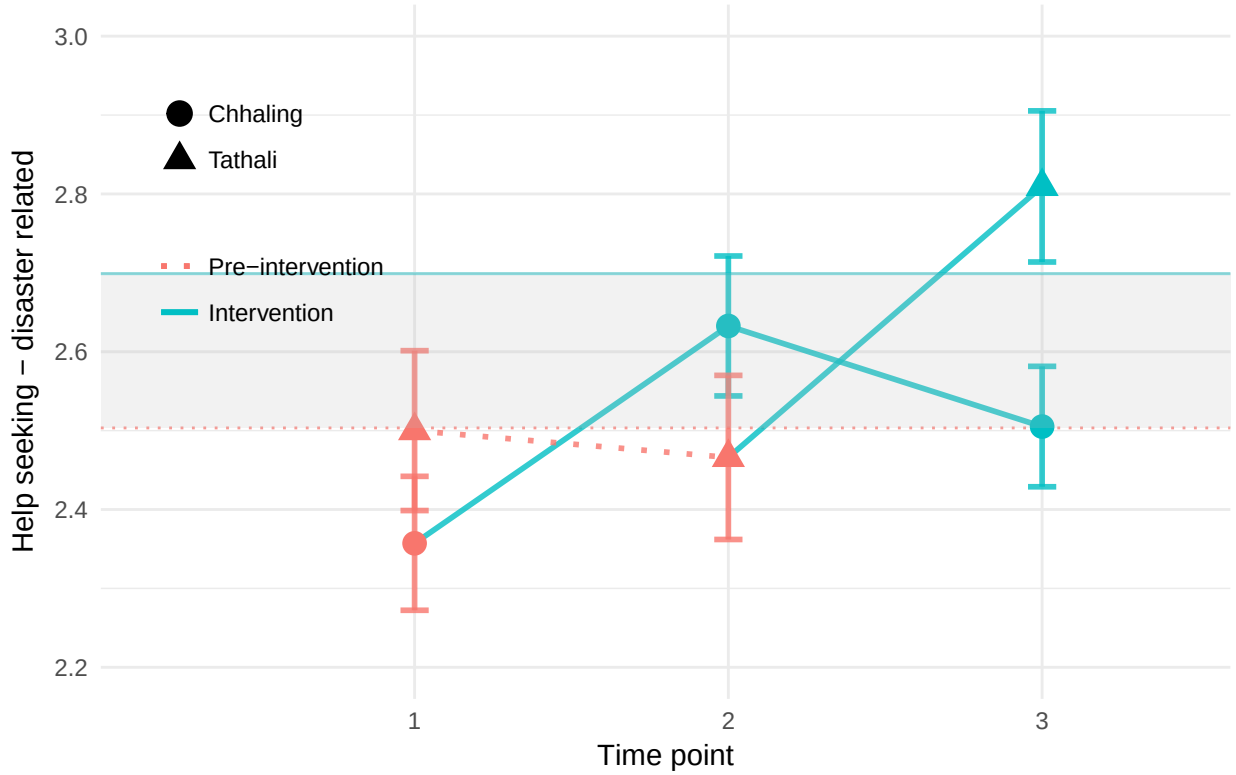
```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       2.503443 0.07856244 527.44 2.349110 2.657777
##  Intervention  2.698875 0.08013928 537.09 2.541444 2.856306
##
## Results are averaged over the levels of: timePoint, gender
## Degrees-of-freedom method: satterthwaite
## Results are given on the as.numeric (not the response) scale.
## Confidence level used: 0.95
```

```
limits <- c(2.2, 3)
theme <- theme_minimal()
rnge <- range(as.numeric(filtered$HelpSeekingDisT), na.rm = TRUE)
caption = "Greater values indicate greater willingness to seek help from to prepare for or after a disa
plot_line_bar("HelpSeekingDisT", limits, mmeans, theme, "Help seeking - disaster related", position=c(.
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```



Greater values indicate greater willingness to seek help from to prepare for or after a disaster (sin
range 1 − 4). Shaded region depicts size of difference between pre− and post−intervention margi

```
help_distCity <- clmm(HelpSeekingDisT ~ timePoint * city + (1|ID), data=filtered)
Anova(help_distCity, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingDisT
##                LR Chisq Df Pr(>Chisq)
## timePoint        0.0000  2   1.000000
## city             0.0000  1   0.999812
## timePoint:city   9.6518  2   0.008019 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
help_distCityMM <- lsmeans::lsmeans(help_distCity, ~ timePoint * city)
summary(rbind(pairs(help_distCityMM, by="city")[c(1,3,4,6)], pairs(help_distCityMM, by="timePoint")))
```

```
##  timePoint contrast           city        estimate        SE df z.ratio
##  .         1 - 2              Chhaling -0.63467132 0.2685290 NA  -2.364
##  .         2 - 3              Chhaling  0.27417445 0.2636648 NA   1.040
##  .         1 - 2              Tathali   0.06240991 0.2793886 NA   0.223
##  .         2 - 3              Tathali  -0.91357042 0.2800190 NA  -3.263
##  1         Chhaling - Tathali .        -0.27253124 0.3329321 NA  -0.819
##  2         Chhaling - Tathali .         0.42454998 0.3341001 NA   1.271
##  3         Chhaling - Tathali .        -0.76319488 0.3294972 NA  -2.316
##  p.value
##   0.1267
##   1.0000
```

```
##   1.0000
##   0.0077
##   1.0000
##   1.0000
##   0.1438
##
## P value adjustment: bonferroni method for 7 tests
```

```
mA <- lmer(socialCohesionT ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- lmer(socialCohesionT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
m <- lmer(socialCohesionT ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
exactRLRT(m=m, mA=mA, m0=m0)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 5.0118, p-value = 0.0047
```

```
# tells us the city random effect is indeed needed; we'll take mA
soc_coh <- mA

summary(soc_coh)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
## Formula: socialCohesionT ~ timePoint * gender + interventionT * gender +
##     (1 | city/ID)
##    Data: filtered
##
## REML criterion at convergence: 2438.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.99646 -0.56086  0.04125  0.61988  2.53190
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID:city  (Intercept) 0.9579   0.9787
##  city     (Intercept) 0.1644   0.4055
##  Residual             2.6506   1.6281
## Number of obs: 600, groups:  ID:city, 201; city, 2
##
## Fixed effects:
##                                     Estimate Std. Error       df t value
## (Intercept)                           6.6801     0.3320   1.4000  20.123
## timePoint2                           -0.2129     0.2654 412.7000  -0.802
## timePoint3                           -0.6532     0.3945 413.4000  -1.656
## genderMale                            0.3947     0.2796 517.4000   1.412
## interventionTIntervention             1.1959     0.3384 407.9000   3.534
## timePoint2:genderMale                 0.7072     0.4225 448.2000   1.674
## timePoint3:genderMale                 1.5859     0.6296 504.5000   2.519
## genderMale:interventionTIntervention -0.9714     0.5297 543.0000  -1.834
```

```
##                                     Pr(>|t|)
## (Intercept)                         0.011201 *
## timePoint2                          0.423071
## timePoint3                          0.098476 .
## genderMale                          0.158536
## interventionTIntervention           0.000456 ***
## timePoint2:genderMale               0.094856 .
## timePoint3:genderMale               0.012088 *
## genderMale:interventionTIntervention 0.067202 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
## timePoint2  -0.233
## timePoint3  -0.156  0.746
## genderMale  -0.301  0.283  0.194
## intrvntnTIn -0.001 -0.641 -0.858 -0.009
## tmPnt2:gndM  0.146 -0.601 -0.432 -0.486  0.359
## tmPnt3:gndM  0.098 -0.427 -0.571 -0.326  0.473  0.717
## gndrMl:ntTI  0.000  0.362  0.483  0.000 -0.563 -0.595 -0.842
```

```
Anova(help_dist, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingDisT
##                       LR Chisq Df Pr(>Chisq)
## timePoint              0.0000  2    1.00000
## gender                 0.0000  1    1.00000
## interventionT          0.0000  1    1.00000
## timePoint:gender       7.5204  2    0.02328 *
## gender:interventionT   4.5235  1    0.03343 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
mmeans <- lsmeans::lsmeans(soc_coh, ~interventionT)  #marginal means
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

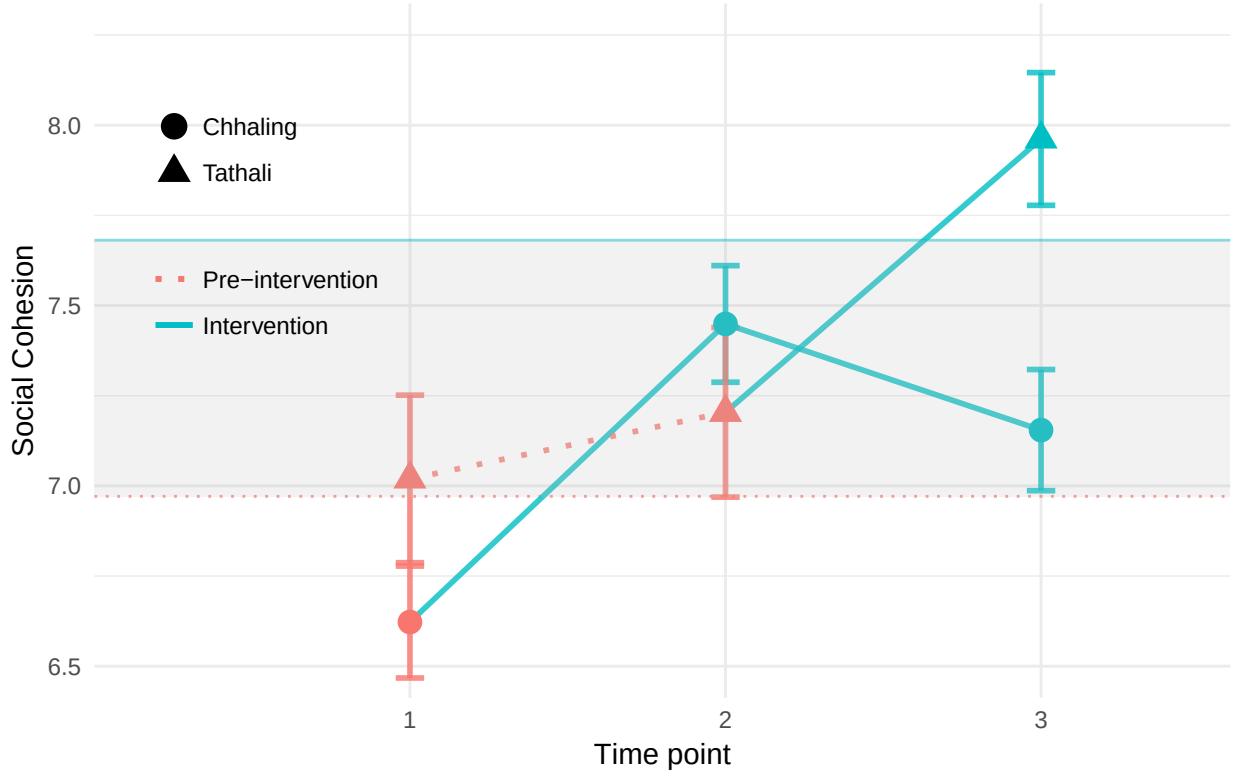
```
summary(mmeans)
```

```
##  interventionT   lsmean        SE   df lower.CL upper.CL
##  Control       6.970932 0.3362207 1.44 4.827508 9.114356
##  Intervention  7.681126 0.3365704 1.45 5.535473 9.826779
##
## Results are averaged over the levels of: timePoint, gender
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```
limits <- c(6.5,8.25)
theme <- theme_minimal()
rnge <- range(filtered$socialCohesionT, na.rm = TRUE)
caption = "Two-item scale (range %d - %d) with greater values indicating greater social cohesion.  Shad
plot_line_bar("socialCohesionT", limits, mmeans, theme, "Social Cohesion", position=c(.15,.68), caption
```

```
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_summary).
## Warning: Removed 4 rows containing non-finite values (stat_summary).
```



Two−item scale (range 2 − 10) with greater values indicating greater social cohesion. Shaded reg
size of difference between pre− and post−intervention marginal means.

```
soc_cohCity <- lmer(socialCohesionT ~ timePoint * city + (1|ID), data=filtered)
Anova(soc_cohCity, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: socialCohesionT
##                    Chisq Df Pr(>Chisq)
## (Intercept)    1133.9651  1  < 2.2e-16 ***
## timePoint        12.5176  2   0.001914 **
## city              2.0285  1   0.154374
## timePoint:city   10.2983  2   0.005804 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
soc_cohCityMM <- lsmeans::lsmeans(soc_cohCity, ~ timePoint * city)
summary(rbind(pairs(soc_cohCityMM, by="city")[c(1,3,4,6)], pairs(soc_cohCityMM, by="timePoint")))
```

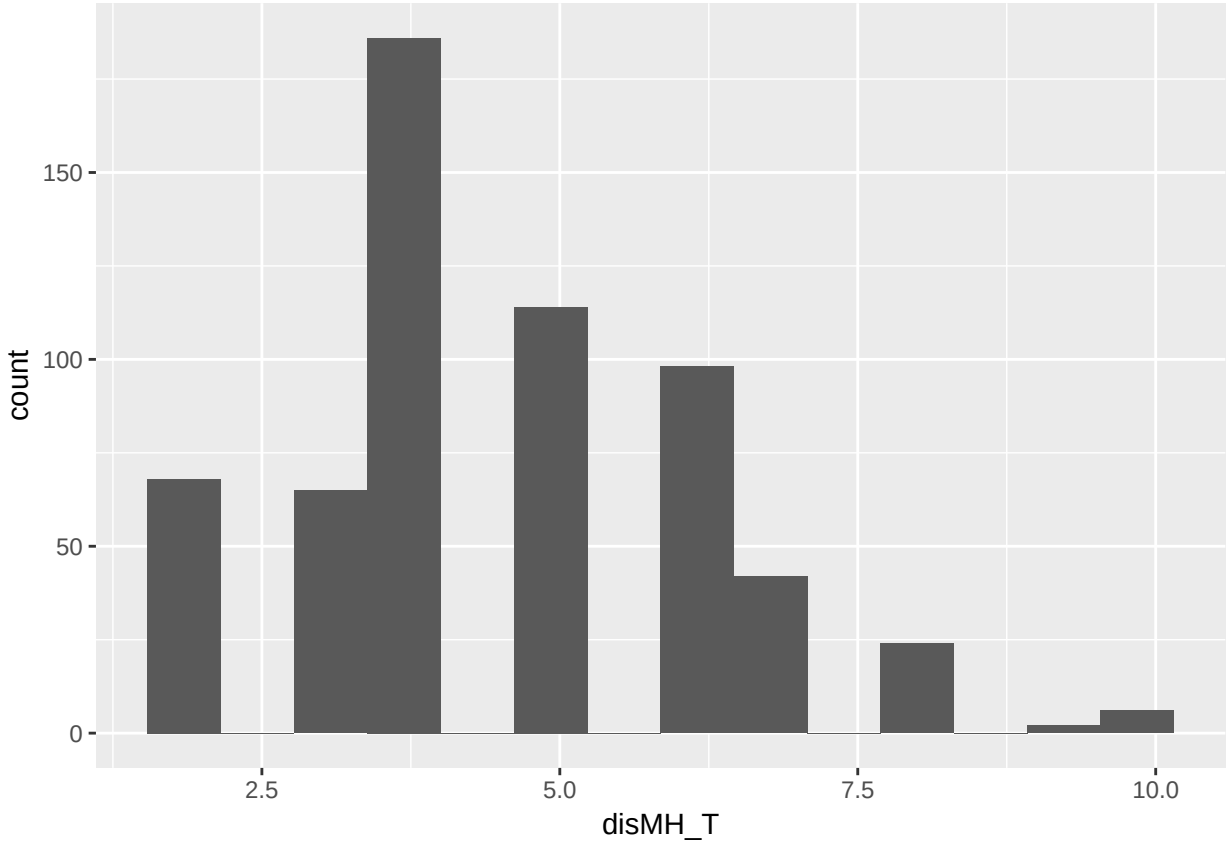
```
##  timePoint contrast           city       estimate        SE     df t.ratio
##  .         1 - 2              Chhaling -0.8265306 0.2370208 396.85  -3.487
##  .         2 - 3              Chhaling  0.2900678 0.2377618 397.80   1.220
##  .         1 - 2              Tathali  -0.1850284 0.2309997 399.54  -0.801
##  .         2 - 3              Tathali  -0.7641744 0.2303303 398.63  -3.318
##  1         Chhaling - Tathali .        -0.3902530 0.2740058 521.77  -1.424
##  2         Chhaling - Tathali .         0.2512493 0.2745749 522.77   0.915
```

```
##  3         Chhaling - Tathali .        -0.8029930 0.2740889 521.92  -2.930
##  p.value
##   0.0038
##   1.0000
##   1.0000
##   0.0069
##   1.0000
##   1.0000
##   0.0248
##
## P value adjustment: bonferroni method for 7 tests
```

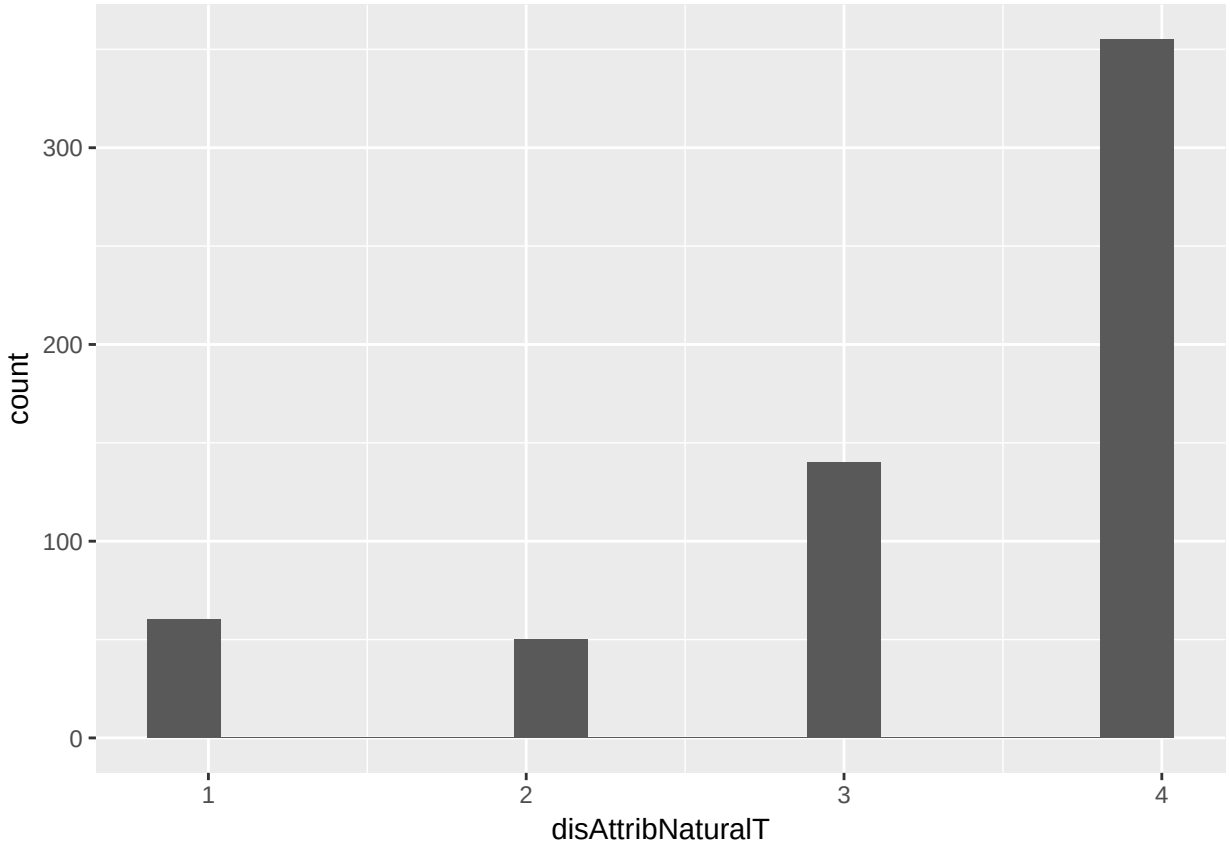
We'll do our other models without plotting the results. First let's look at their distributions.

```
dvs = c('disMH_T', 'disAttribNaturalT', 'disAttribGodT', 'disAttribKarmaT', 'HelpGivingDisT', 'HelpGivi
var=dvs[1]
for(var in dvs) {
  print(ggplot(data = filtered, aes_string(x=var)) + geom_histogram(bins=14))
}
```

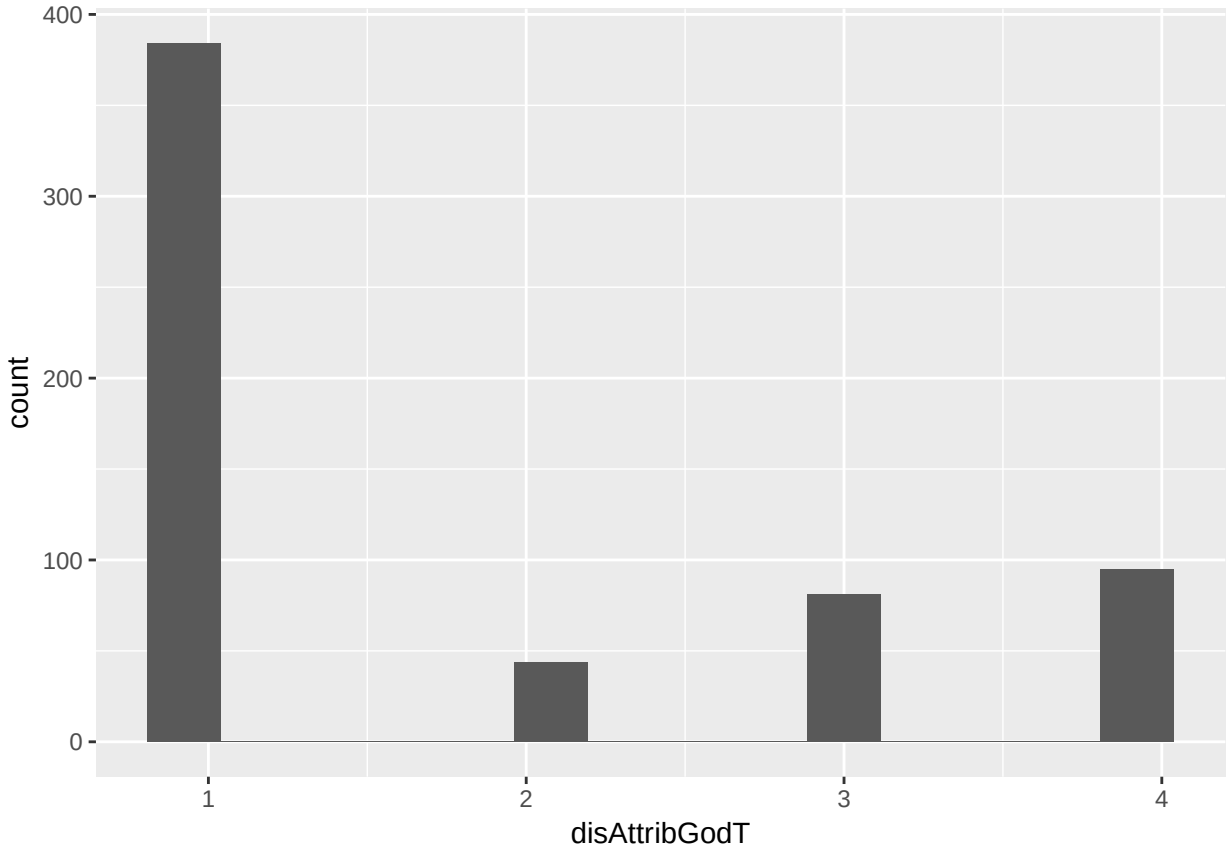
```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



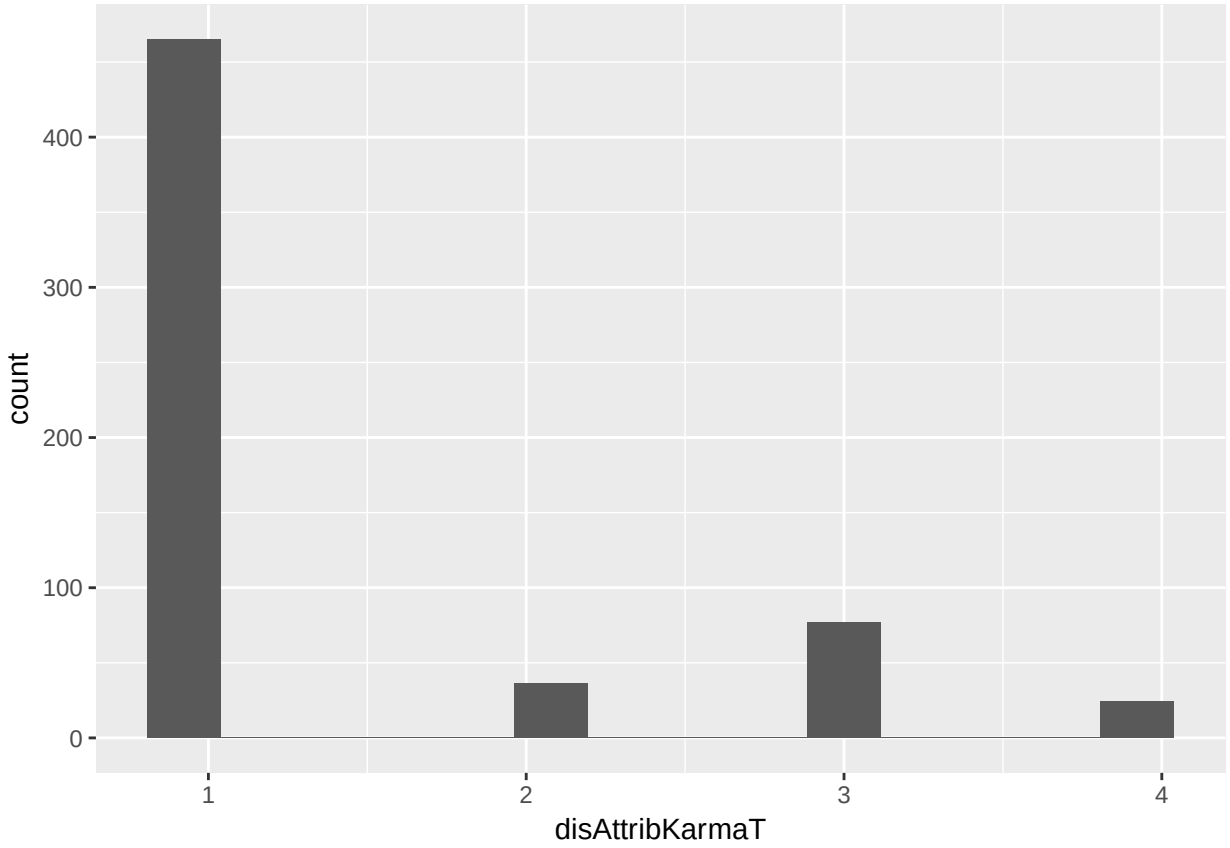

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



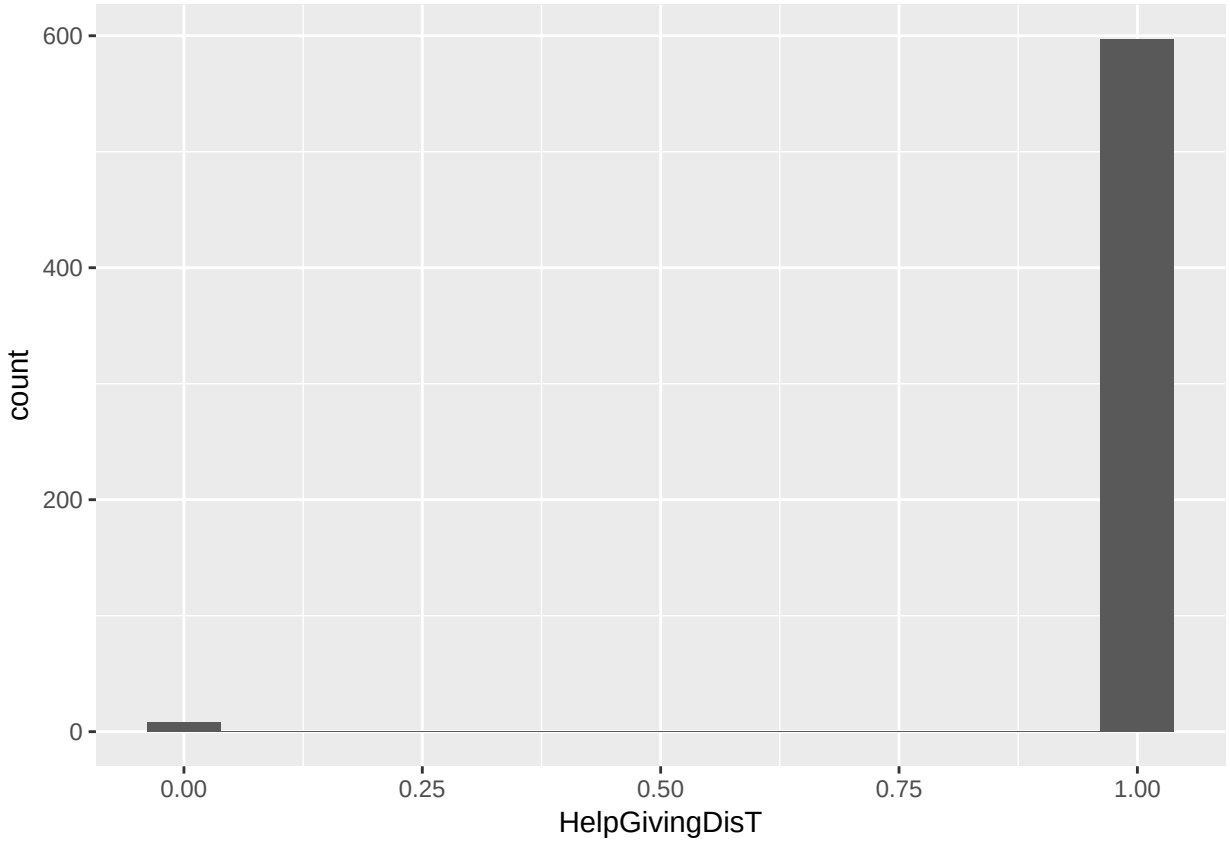

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```



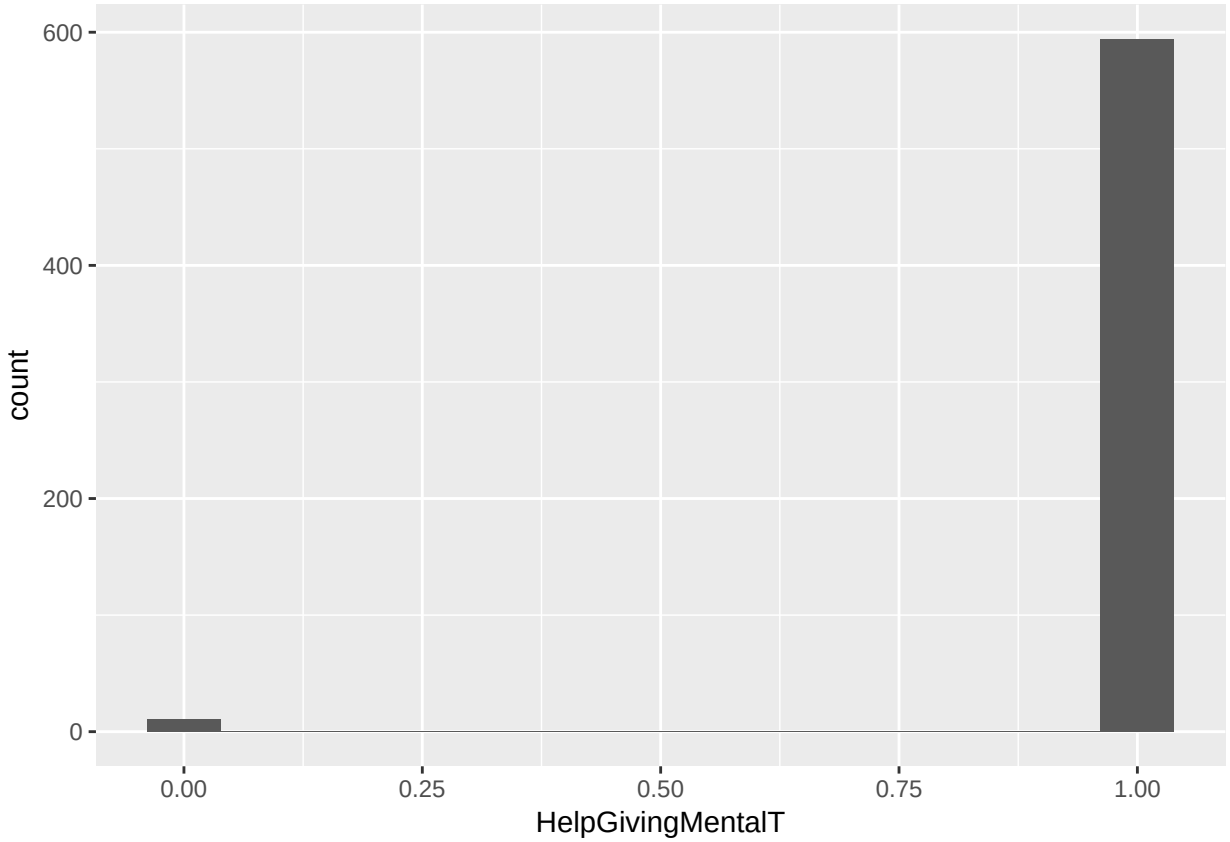

```
## Warning: Removed 7 rows containing non-finite values (stat_bin).
```



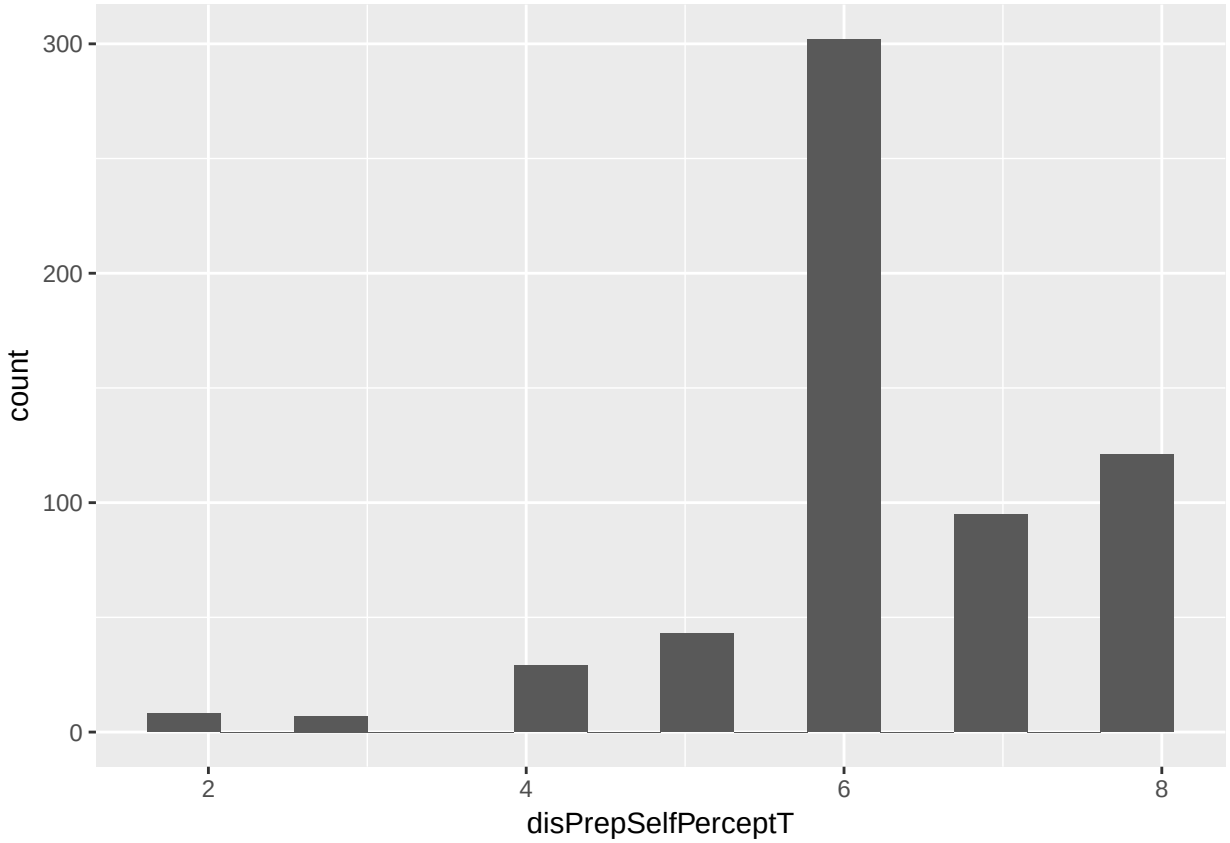

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



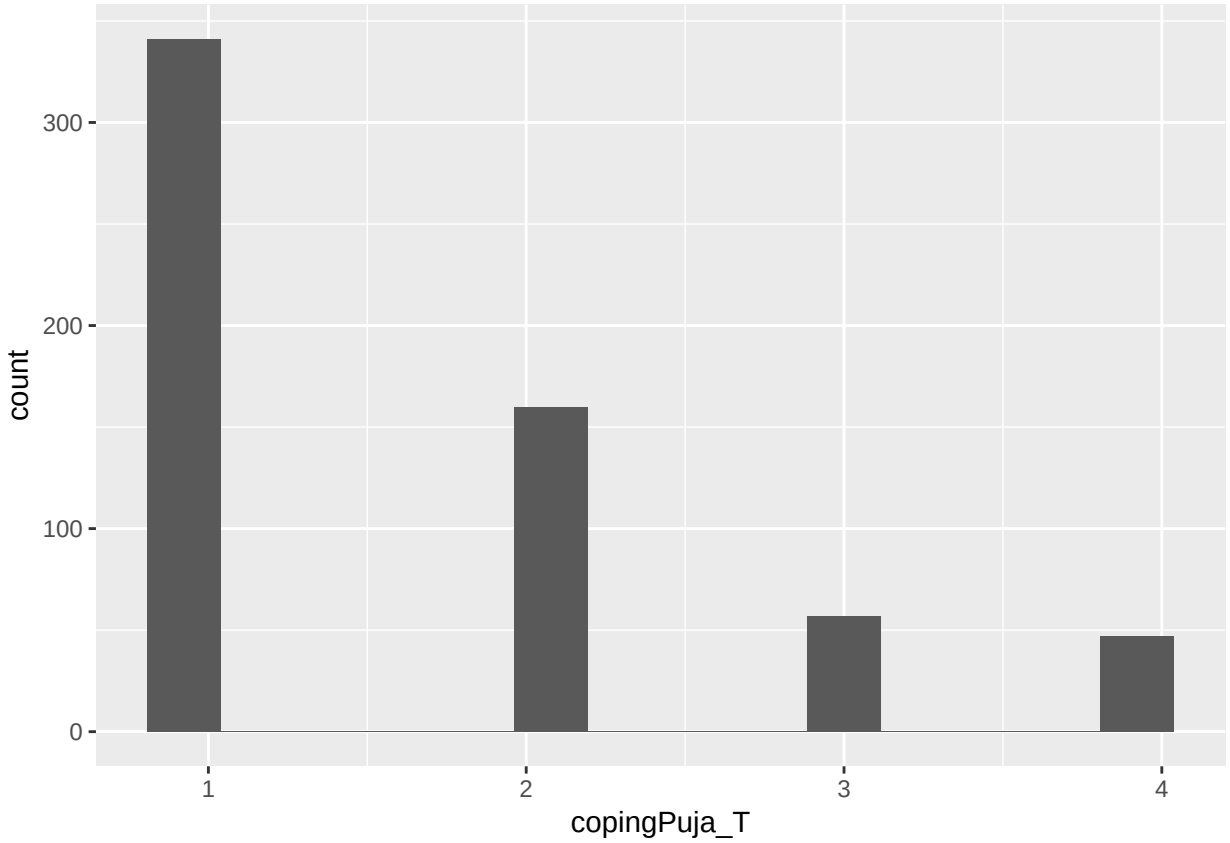

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



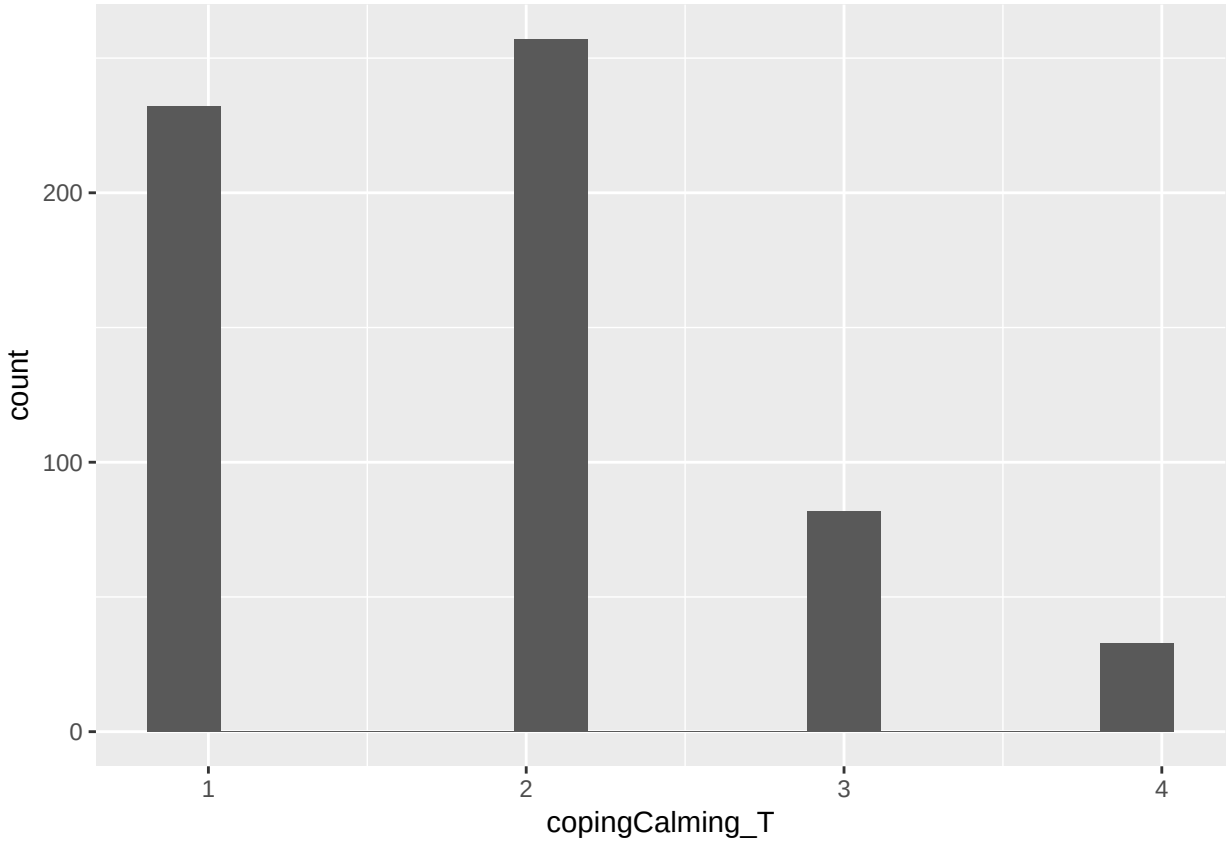

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



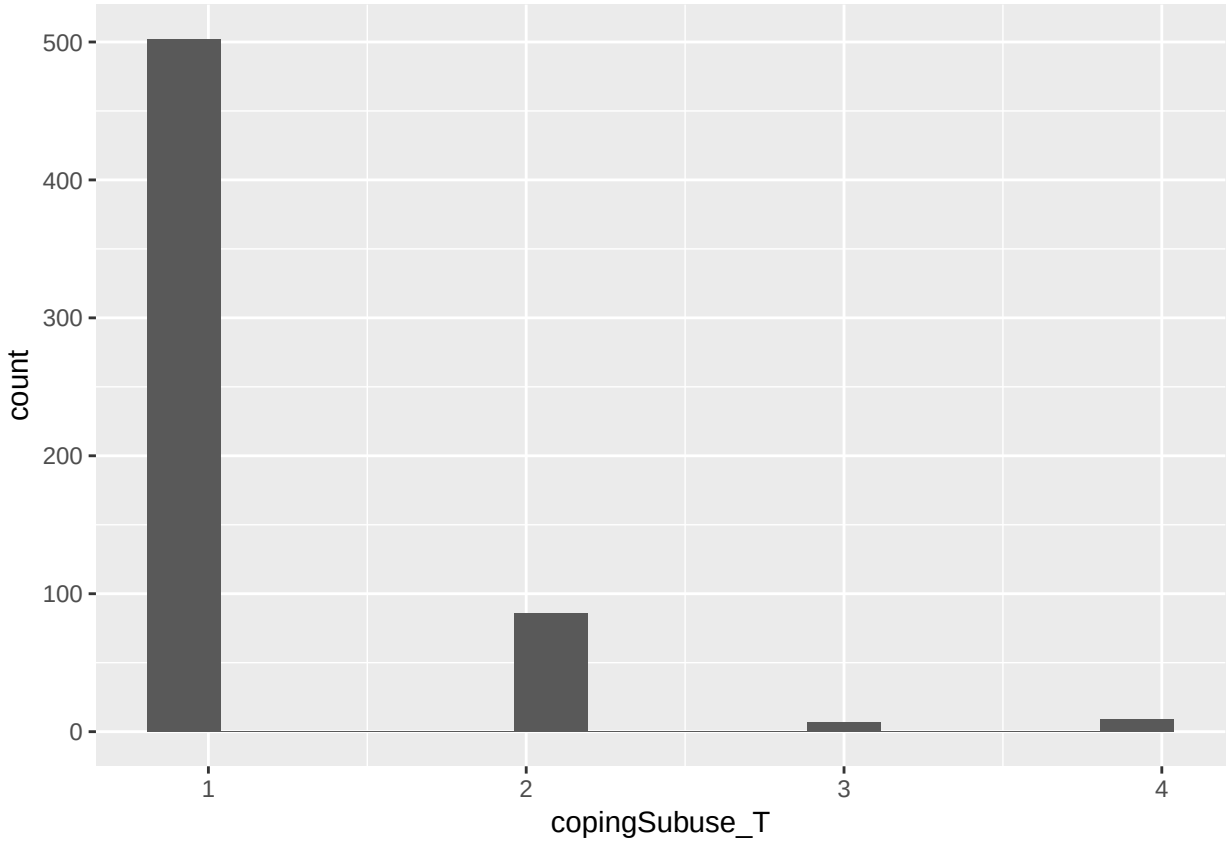

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



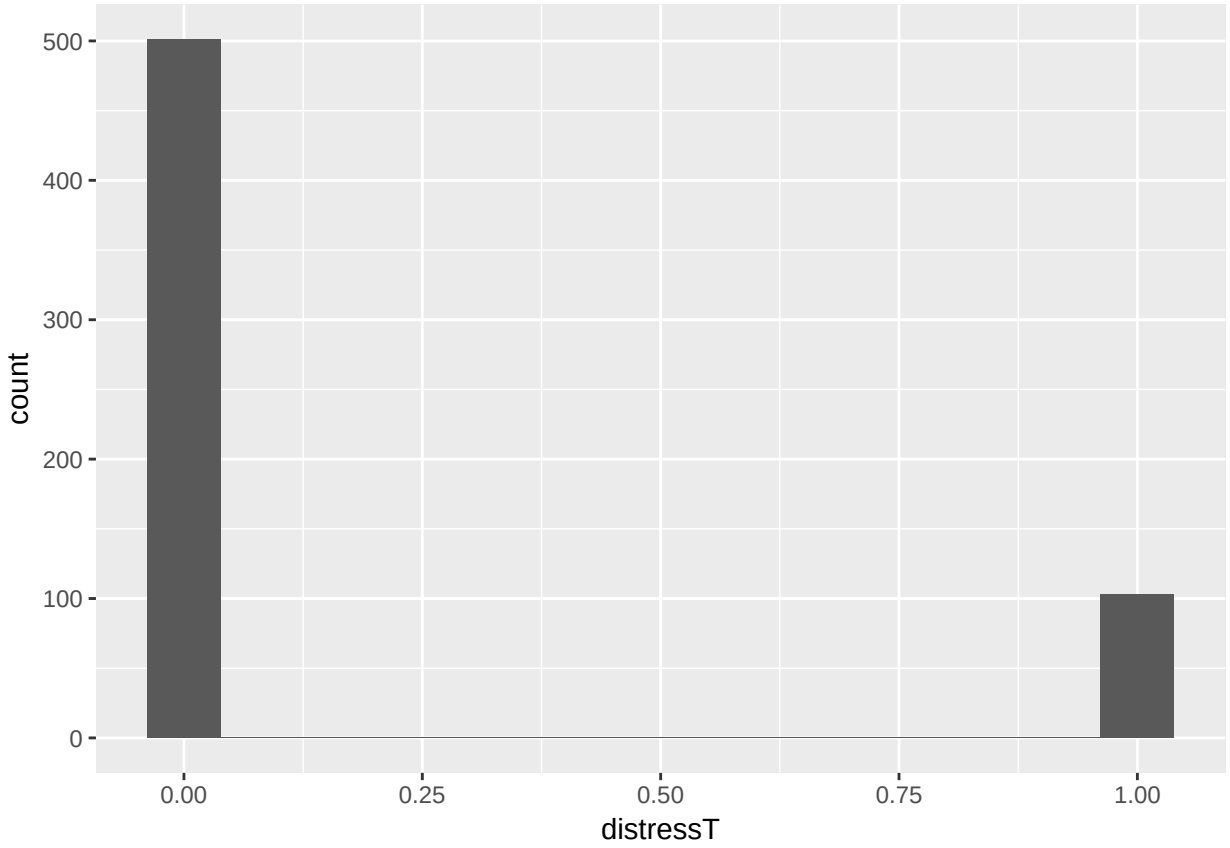

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```



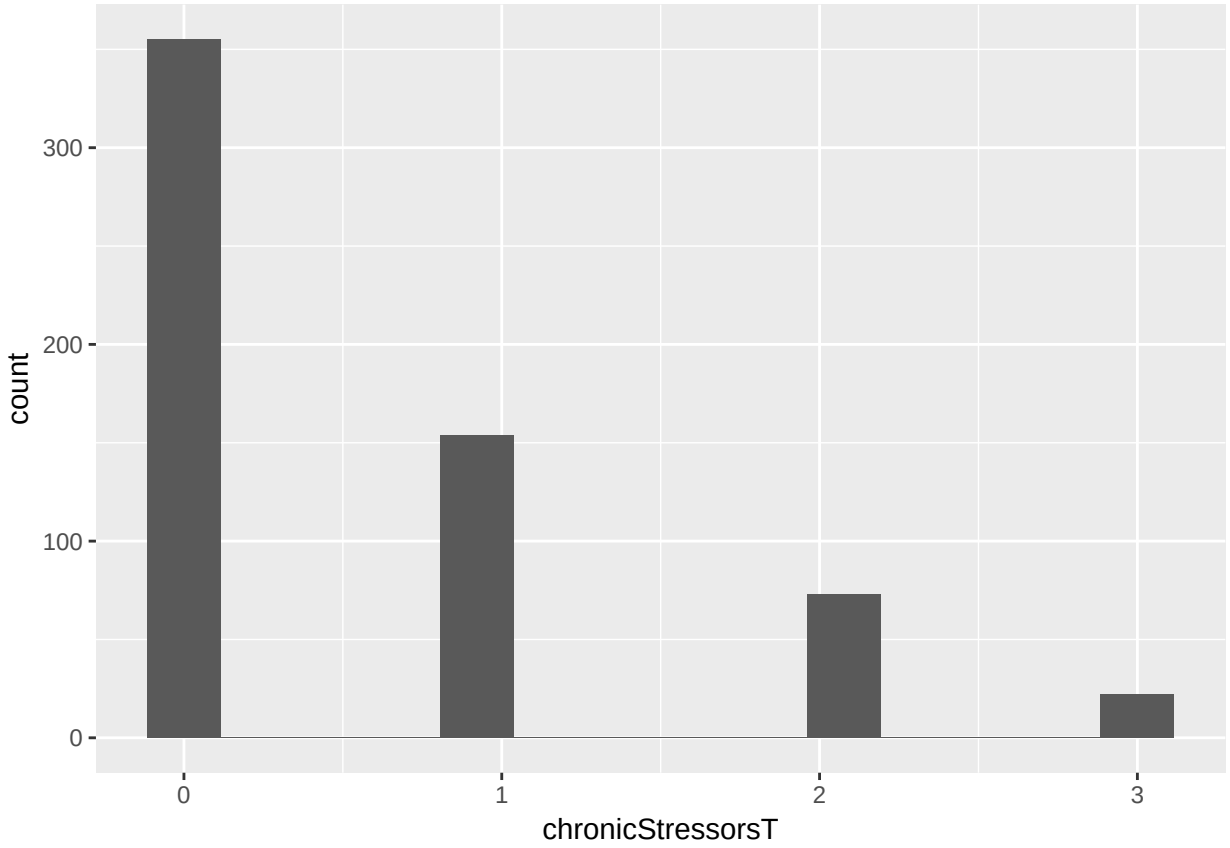

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```




```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```




```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```



Disaster-related mental health concerns seeems relatively normally-distributed; disaster attribution variables are not well distributed and might be best approximated by cumulative logit / probit models; help giving - disaster related and help giving - mental health related appear to have near-zero variance and will not be analyzed; disaster-related self perception is not very normally distributed but a linear model may suffice; chronic stressors & coping variables are not well distributed and might be best approximated by cumulative logit / probit models, with substance abuse coping not displaying much variance; distress is a logistic process.

```
#factor_dvs <- c('disAttribNaturalT', 'disAttribGodT', 'disAttribKarmaT','disPrepSelfPerceptT', 'coping
factor_dvs <- c('disAttribNaturalT', 'disAttribGodT', 'disAttribKarmaT', 'copingPuja_T', 'copingCalming_
filtered %<>% mutate_at(factor_dvs, funs(factor(.)))

mA <- lmer(disMH_T ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- lmer(disMH_T ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
m <- lmer(disMH_T ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
exactRLRT(m=m, mA=mA, m0=m0)
```

```
##
##  simulated finite sample distribution of RLRT.
##
##  (p-value based on 10000 simulated values)
##
## data:
## RLRT = 0, p-value = 1
```

```
# tells us the city random effect is not needed; we'll take m0
disMH <- m0
summary(disMH)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
## Formula: disMH_T ~ timePoint * gender + interventionT * gender + (1 |
##     ID)
##    Data: filtered
##
## REML criterion at convergence: 2223.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3028 -0.5808 -0.0955  0.5766  3.6872
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.6639   0.8148
##  Residual             1.8538   1.3615
## Number of obs: 600, groups:  ID, 201
##
## Fixed effects:
##                                     Estimate Std. Error       df t value
## (Intercept)                           5.1860     0.1397 520.3000  37.122
## timePoint2                           -0.2763     0.2166 454.2000  -1.275
## timePoint3                           -0.3166     0.3151 504.1000  -1.005
## genderMale                           -0.9499     0.2334 520.3000  -4.070
## interventionTIntervention            -0.2725     0.2657 543.7000  -1.026
## timePoint2:genderMale                 0.6645     0.3532 449.6000   1.881
## timePoint3:genderMale                 0.3656     0.5264 505.9000   0.694
## genderMale:interventionTIntervention -0.1804     0.4427 544.3000  -0.407
##                                     Pr(>|t|)
## (Intercept)                          < 2e-16 ***
## timePoint2                            0.2028
## timePoint3                            0.3156
## genderMale                           5.44e-05 ***
## interventionTIntervention             0.3054
## timePoint2:genderMale                 0.0606 .
## timePoint3:genderMale                 0.4877
## genderMale:interventionTIntervention  0.6838
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
## timePoint2  -0.475
## timePoint3  -0.326  0.731
## genderMale  -0.599  0.284  0.195
## intrvntnTIn  0.000 -0.618 -0.843  0.000
## tmPnt2:gndM  0.291 -0.613 -0.449 -0.487  0.379
## tmPnt3:gndM  0.195 -0.438 -0.599 -0.327  0.505  0.717
## gndrMl:ntTI  0.000  0.371  0.506  0.000 -0.600 -0.595 -0.842
```

```
Anova(disMH, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: disMH_T
```

```
##                          Chisq Df Pr(>Chisq)
## (Intercept)          1378.0404  1  < 2.2e-16 ***
## timePoint               1.6379  2     0.4409
## gender                 16.5620  1  4.708e-05 ***
## interventionT           1.0525  1     0.3049
## timePoint:gender        4.4173  2     0.1098
## gender:interventionT    0.1660  1     0.6837
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#mA <- clmm(disAttribNaturalT  ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filter
m0 <- clmm(disAttribNaturalT  ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(disAttribNaturalT  ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
disAttribNatural <- m0
summary(disAttribNatural)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula:
## disAttribNaturalT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  600  -600.92 1223.84 772(3079) 6.93e-04 3.1e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 2.465    1.57
## Number of groups:  ID 201
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## timePoint2                            -0.5220     0.3332  -1.567   0.1172
## timePoint3                            -0.6550     0.4915  -1.333   0.1827
## genderMale                             0.8859     0.4166   2.127   0.0335
## interventionTIntervention              1.0134     0.4205   2.410   0.0160
## timePoint2:genderMale                  0.3571     0.6004   0.595   0.5520
## timePoint3:genderMale                  0.6805     0.9671   0.704   0.4816
## genderMale:interventionTIntervention   0.4899     0.8150   0.601   0.5478
##
## timePoint2
## timePoint3
## genderMale                           *
## interventionTIntervention            *
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
```

```
## 1|2 -2.59632    0.28284  -9.180
## 2|3 -1.65752    0.25581  -6.480
## 3|4  0.03974    0.23772   0.167
## (9 observations deleted due to missingness)
```

```
Anova(disAttribNatural, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: disAttribNaturalT
##                       LR Chisq Df Pr(>Chisq)
## timePoint             0.00000  2     1.0000
## gender                0.00000  1     1.0000
## interventionT         0.00000  1     0.9999
## timePoint:gender      0.52109  2     0.7706
## gender:interventionT  0.36483  1     0.5458
```

```
#mA <- clmm(disAttribGodT ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- clmm(disAttribGodT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(disAttribGodT ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is needed; we'll take mA
disAttribGod <- m0 # as m0 because clmm wont run with nested random effects here
summary(disAttribGod)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: disAttribGodT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  599  -539.61 1101.23 745(5914) 2.71e-03 3.5e+03
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 6.402    2.53
## Number of groups:  ID 201
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## timePoint2                          -0.6375     0.4010  -1.590    0.112
## timePoint3                          -0.6697     0.5802  -1.154    0.248
## genderMale                          -2.0590     0.4951  -4.158 3.21e-05
## interventionTIntervention           -0.4929     0.5056  -0.975    0.330
## timePoint2:genderMale                0.7339     0.7077   1.037    0.300
## timePoint3:genderMale                0.2176     1.0585   0.206    0.837
## genderMale:interventionTIntervention -0.1444     0.9049  -0.160    0.873
##
## timePoint2
## timePoint3
## genderMale                          ***
## interventionTIntervention
## timePoint2:genderMale
## timePoint3:genderMale
```

```
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2 -0.09771    0.32420  -0.301
## 2|3  0.55687    0.32420   1.718
## 3|4  2.05387    0.33781   6.080
## (10 observations deleted due to missingness)
```

```
Anova(disAttribGod, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: disAttribGodT
##                       LR Chisq Df Pr(>Chisq)
## timePoint            -0.03330  2     1.0000
## gender               -0.03462  1     1.0000
## interventionT         0.34297  1     0.5581
## timePoint:gender      1.70656  2     0.4260
## gender:interventionT -0.00079  1     1.0000
```

```
#mA <- clmm(disAttribKarmaT  ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- clmm(disAttribKarmaT  ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(disAttribKarmaT  ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
disAttribKarma  <- m0
summary(disAttribKarma )
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: disAttribKarmaT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC    niter     max.grad cond.H
##  logit flexible  597  -415.52 853.04 704(3872) 1.30e-04 8.2e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 3.064    1.75
## Number of groups:  ID 201
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## timePoint2                            0.57935    0.38740   1.495   0.1348
## timePoint3                            1.08176    0.60265   1.795   0.0727
## genderMale                           -1.45280    0.56693  -2.563   0.0104
## interventionTIntervention            -1.19447    0.51447  -2.322   0.0202
## timePoint2:genderMale                -0.31573    0.80265  -0.393   0.6941
## timePoint3:genderMale                 0.68316    1.27248   0.537   0.5914
## genderMale:interventionTIntervention -0.06398    1.10183  -0.058   0.9537
##
```

```
## timePoint2
## timePoint3                          .
## genderMale                          *
## interventionTIntervention           *
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2   1.5092     0.3140   4.807
## 2|3   2.0671     0.3313   6.239
## 3|4   4.1468     0.4260   9.734
## (12 observations deleted due to missingness)
```

```
Anova(disAttribKarma , type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: disAttribKarmaT
##                       LR Chisq Df Pr(>Chisq)
## timePoint             0.00000  2     1.0000
## gender                0.00000  1     1.0000
## interventionT         0.00000  1     1.0000
## timePoint:gender      1.43281  2     0.4885
## gender:interventionT  0.00338  1     0.9536
```

```
#linear dis prep self perception
#mA <- clmm(disPrepSelfPerceptT  ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filt
#m0 <- clmm(disPrepSelfPerceptT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
m0 <- lmer(disPrepSelfPerceptT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(disPrepSelfPerceptT ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
disPrep_selfPercept <- m0
summary(disPrep_selfPercept)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
## Formula:
## disPrepSelfPerceptT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
##    Data: filtered
##
## REML criterion at convergence: 1870.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.0221 -0.4847  0.0405  0.6230  1.8387
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.3231   0.5684
```

```
##  Residual             1.0468   1.0231
## Number of obs: 600, groups:  ID, 201
##
## Fixed effects:
##                                     Estimate Std. Error        df
## (Intercept)                          5.91473    0.10305 533.70000
## timePoint2                           0.28474    0.16233 458.40000
## timePoint3                           0.46867    0.23557 510.70000
## genderMale                           0.11305    0.17218 533.70000
## interventionTIntervention            0.22901    0.19815 551.40000
## timePoint2:genderMale               -0.17594    0.26474 453.50000
## timePoint3:genderMale                0.02046    0.39344 512.50000
## genderMale:interventionTIntervention -0.01185    0.33022 552.00000
##                                     t value Pr(>|t|)
## (Intercept)                          57.397   <2e-16 ***
## timePoint2                            1.754   0.0801 .
## timePoint3                            1.990   0.0472 *
## genderMale                            0.657   0.5117
## interventionTIntervention             1.156   0.2483
## timePoint2:genderMale                -0.665   0.5067
## timePoint3:genderMale                 0.052   0.9586
## genderMale:interventionTIntervention -0.036   0.9714
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
## timePoint2  -0.485
## timePoint3  -0.334  0.730
## genderMale  -0.599  0.290  0.200
## intrvntnTIn  0.000 -0.615 -0.841  0.000
## tmPnt2:gndM  0.297 -0.613 -0.447 -0.497  0.377
## tmPnt3:gndM  0.200 -0.437 -0.599 -0.334  0.504  0.715
## gndrMl:ntTI  0.000  0.369  0.505  0.000 -0.600 -0.592 -0.840
```

```
Anova(disPrep_selfPercept, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: disPrepSelfPerceptT
##                          Chisq Df Pr(>Chisq)
## (Intercept)          3294.3705  1     <2e-16 ***
## timePoint               4.1538  2     0.1253
## gender                  0.4311  1     0.5115
## interventionT           1.3357  1     0.2478
## timePoint:gender        1.0101  2     0.6035
## gender:interventionT    0.0013  1     0.9714
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#mA <- clmm(copingPuja_T ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- clmm(copingPuja_T ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(copingPuja_T ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is needed; we'll take mA
```

```r
copingPuja <- m0
summary(copingPuja)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: copingPuja_T ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  600  -580.76 1183.53 753(4716) 7.64e-05 3.2e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 5.757    2.399
## Number of groups:  ID 201
##
## Coefficients:
##                                     Estimate Std. Error z value Pr(>|z|)
## timePoint2                          -0.29528    0.37848  -0.780   0.4353
## timePoint3                          -0.27022    0.56262  -0.480   0.6310
## genderMale                          -0.63966    0.51874  -1.233   0.2175
## interventionTIntervention            0.03914    0.48185   0.081   0.9353
## timePoint2:genderMale                1.10273    0.63571   1.735   0.0828
## timePoint3:genderMale                0.93293    0.94902   0.983   0.3256
## genderMale:interventionTIntervention -0.71735    0.80126  -0.895   0.3706
##
## timePoint2
## timePoint3
## genderMale
## interventionTIntervention
## timePoint2:genderMale                .
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2   0.2701     0.3133   0.862
## 2|3   2.6338     0.3503   7.518
## 3|4   4.0911     0.3977  10.288
## (9 observations deleted due to missingness)
```

```r
Anova(copingPuja, type="III")
```

```
## Warning in update.uC(rho): iteration limit reached when updating the random effects
##   at iteration 286
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: copingPuja_T
##                      LR Chisq Df Pr(>Chisq)
## timePoint              0.0000  2     1.0000
## gender                 0.0000  1     0.9999
```

```
## interventionT          0.0000  1     1.0000
## timePoint:gender       3.2899  2     0.1930
## gender:interventionT   0.8056  1     0.3694
```

```
#mA <- clmm(copingCalming_T ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- clmm(copingCalming_T ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(copingCalming_T  ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
copingCalming <- m0
summary(copingCalming)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: copingCalming_T ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  599  -645.88 1313.76 821(2466) 7.84e-04 1.9e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 1.317    1.147
## Number of groups:  ID 201
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## timePoint2                          0.08360    0.34165   0.245 0.806689
## timePoint3                          0.21795    0.46448   0.469 0.638910
## genderMale                         -0.24281    0.36370  -0.668 0.504386
## interventionTIntervention           1.33572    0.39499   3.382 0.000721
## timePoint2:genderMale               0.13860    0.56468   0.245 0.806113
## timePoint3:genderMale              -0.26385    0.78302  -0.337 0.736139
## genderMale:interventionTIntervention  0.09398    0.65188   0.144 0.885371
##
## timePoint2
## timePoint3
## genderMale
## interventionTIntervention           ***
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2  0.04146    0.21699   0.191
## 2|3  2.62873    0.25828  10.178
## 3|4  4.34481    0.32983  13.173
## (10 observations deleted due to missingness)
```

```r
Anova(copingCalming, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: copingCalming_T
##                       LR Chisq Df Pr(>Chisq)
## timePoint             0.00000  2     1.0000
## gender                0.00000  1     1.0000
## interventionT         0.00000  1     1.0000
## timePoint:gender      0.71738  2     0.6986
## gender:interventionT  0.02079  1     0.8853
```

```r
#mA <- clmm(copingSubuse_T  ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtered)
m0 <- clmm(copingSubuse_T  ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(copingSubuse_T   ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
copingSubuse <- m0
summary(copingSubuse)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: copingSubuse_T ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC    niter     max.grad cond.H
##  logit flexible  599  -252.17 526.33 727(5700) 3.19e-06 1.0e+03
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 24.77    4.977
## Number of groups:  ID 201
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## timePoint2                          -0.7562     0.7417  -1.020  0.30794
## timePoint3                          -1.5993     1.1965  -1.337  0.18132
## genderMale                           2.3954     0.9148   2.618  0.00883
## interventionTIntervention            0.6144     0.9880   0.622  0.53401
## timePoint2:genderMale               -0.5082     0.9830  -0.517  0.60517
## timePoint3:genderMale                0.8320     1.5880   0.524  0.60034
## genderMale:interventionTIntervention -1.0579     1.3581  -0.779  0.43600
##
## timePoint2
## timePoint3
## genderMale                          **
## interventionTIntervention
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2    5.811      1.050   5.532
## 2|3    9.866      1.360   7.253
## 3|4   10.517      1.394   7.544
## (10 observations deleted due to missingness)
```

```
Anova(copingSubuse, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: copingSubuse_T
##                       LR Chisq Df Pr(>Chisq)
## timePoint             0.00000  2     1.0000
## gender                0.00000  1     1.0000
## interventionT         0.00000  1     1.0000
## timePoint:gender      1.82978  2     0.4006
## gender:interventionT  0.61833  1     0.4317
```

```
#mA <- clmm(chronicStressorsT ~ timePoint * gender + interventionT * gender + (1|city/ID), data=filtere
m0 <- clmm(chronicStressorsT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered)
#m <- clmm(chronicStressorsT ~ timePoint * gender + interventionT * gender + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
chronicStressors <- m0
summary(chronicStressors)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula:
## chronicStressorsT ~ timePoint * gender + interventionT * gender +
##     (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  599  -560.82 1143.64 712(4319) 3.74e-04 2.8e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 3.76     1.939
## Number of groups:  ID 201
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## timePoint2                         -0.77672    0.37589  -2.066   0.0388
## timePoint3                         -1.06175    0.55945  -1.898   0.0577
## genderMale                         -0.14764    0.44111  -0.335   0.7378
## interventionTIntervention          -0.26264    0.47066  -0.558   0.5768
## timePoint2:genderMale               0.49421    0.61362   0.805   0.4206
## timePoint3:genderMale               0.03906    0.89474   0.044   0.9652
## genderMale:interventionTIntervention  0.87271    0.75516   1.156   0.2478
##
## timePoint2                         *
## timePoint3                         .
## genderMale
```

```
## interventionTIntervention
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 0|1  0.01817    0.27261   0.067
## 1|2  2.16627    0.30414   7.123
## 2|3  4.52847    0.41519  10.907
## (10 observations deleted due to missingness)
```

```
Anova(chronicStressors, type="III")
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: chronicStressorsT
##                       LR Chisq Df Pr(>Chisq)
## timePoint               0.0000  2     1.0000
## gender                  0.0000  1     1.0000
## interventionT           0.0000  1     0.9999
## timePoint:gender        1.3649  2     0.5054
## gender:interventionT    1.3360  1     0.2477
```

```
distress <- glmer(distressT ~ timePoint * gender + interventionT * gender + (1|ID), data=filtered, famil
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.00720519 (tol =
## 0.001, component 1)
```

```
summary(distress)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: distressT ~ timePoint * gender + interventionT * gender + (1 |
##     ID)
##    Data: filtered
##
##      AIC      BIC   logLik deviance df.resid
##    517.8    557.4   -249.9    499.8      590
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.1606 -0.2986 -0.2569 -0.1218  3.5430
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 2.686    1.639
## Number of obs: 599, groups:  ID, 201
##
## Fixed effects:
##                                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         -1.8548     0.3451  -5.374 7.69e-08
```

```
## timePoint2                             -0.3186     0.4689  -0.679    0.497
## timePoint3                             -0.5584     0.6800  -0.821    0.412
## genderMale                             -0.2915     0.5003  -0.583    0.560
## interventionTIntervention               0.1627     0.5759   0.282    0.778
## timePoint2:genderMale                  -1.1339     0.9163  -1.238    0.216
## timePoint3:genderMale                  -1.6378     1.4078  -1.163    0.245
## genderMale:interventionTIntervention    0.2741     1.1702   0.234    0.815
##
## (Intercept)                           ***
## timePoint2
## timePoint3
## genderMale
## interventionTIntervention
## timePoint2:genderMale
## timePoint3:genderMale
## genderMale:interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3 gndrMl intrTI tmP2:M tmP3:M
## timePoint2  -0.374
## timePoint3  -0.263  0.734
## genderMale  -0.457  0.261  0.179
## intrvntnTIn  0.029 -0.640 -0.844  0.004
## tmPnt2:gndM  0.261 -0.511 -0.376 -0.375  0.335
## tmPnt3:gndM  0.199 -0.354 -0.484 -0.238  0.415  0.700
## gndrMl:ntTI -0.048  0.315  0.416 -0.008 -0.496 -0.656 -0.841
## convergence code: 0
## Model failed to converge with max|grad| = 0.00720519 (tol = 0.001, component 1)
```

```
Anova(distress, type="III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: distressT
##                         Chisq Df Pr(>Chisq)
## (Intercept)          28.8822  1  7.692e-08 ***
## timePoint             0.6870  2     0.7093
## gender                0.3396  1     0.5601
## interventionT         0.0798  1     0.7776
## timePoint:gender      1.7044  2     0.4265
## gender:interventionT  0.0549  1     0.8148
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Summary plots

Here we'll make a plot of unstandardized regression coefficients for the intervention effects derived from our above mixed models.

```
dv_names <-
c('Disaster preparation behaviors', 'Mean PHQ', 'Mean PTSD', 'Social cohesion', 'Help seeking - mental h
estimates <- c()
```

```r
estimates[1] <- summary(disPrep)$coef[,'Estimate'][4]
estimates[1] <- exp(estimates[1]) / (1 + exp(estimates[1]))
estimates[2] <- summary(phq)$coef[,'Estimate'][4]
estimates[3] <- summary(ptsd)$coef[,'Estimate'][4]
estimates[4] <- summary(soc_coh)$coef[,'Estimate'][4]
estimates[5] <- summary(help_mental)$coef[,'Estimate'][4]
estimates[6] <- summary(help_dist)$coef[,'Estimate'][4]
estimates[7] <- summary(disMH)$coef[,'Estimate'][4]
estimates[8] <- summary(disAttribNatural)$coef[,'Estimate'][4]
estimates[9] <- summary(disAttribGod)$coef[,'Estimate'][4]
estimates[10] <- summary(disAttribKarma)$coef[,'Estimate'][4]
estimates[11] <- summary(disPrep_selfPercept)$coef[,'Estimate'][4]
estimates[12] <- summary(copingPuja)$coef[,'Estimate'][4]
estimates[13] <- summary(copingCalming)$coef[,'Estimate'][4]
estimates[14] <- summary(copingSubuse)$coef[,'Estimate'][4]
#estimates[15] <- summary(distress)$coef[,'Estimate'][4]
#estimates[15] <- exp(estimates[15]) / (1 + exp(estimates[15]))

sds <- c()
sds[1] <- sd(filtered$disPrepBehaviorsT, na.rm = TRUE)
sds[2] <- sd(filtered$phqMean6_T, na.rm = TRUE)
sds[3] <- sd(filtered$ptsdMean11_T, na.rm = TRUE)
sds[4] <- sd(filtered$socialCohesionT, na.rm = TRUE)
sds[5] <- sd(filtered$HelpSeekingMentalT, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```r
sds[6] <- sd(filtered$HelpSeekingDisT, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```r
sds[7] <- sd(filtered$disMH_T, na.rm = TRUE)
sds[8] <- sd(filtered$disAttribNaturalT, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```r
sds[9] <- sd(filtered$disAttribGodT, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```r
sds[10] <- sd(filtered$disAttribKarmaT, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```r
sds[11] <- sd(filtered$disPrepSelfPerceptT, na.rm = TRUE)
sds[12] <- sd(filtered$copingPuja_T, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```r
sds[13] <- sd(filtered$copingCalming_T, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
```

```
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

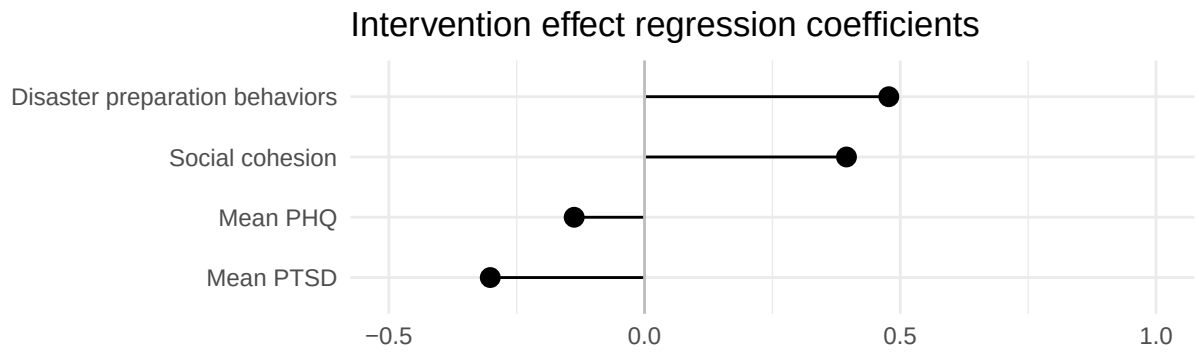
```
sds[14] <- sd(filtered$copingSubuse_T, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm = na.rm): Calling var(x)
##   Use something like 'all(duplicated(x)[-1L])' to test for a constant vector.
```

```
#sds[15] <- sd(filtered$distressT, na.rm = TRUE)

effects <- data.frame(dvs = dv_names, estimates = estimates, sds = sds, stdestimates = estimates/sds)

ggplot(effects[1:4,], aes(x=reorder(dvs,estimates), y=estimates)) +
  geom_point(stat='identity', fill="black", size=3)  +
  geom_segment(aes(y = 0,
                   x = dvs,
                   yend = estimates,
                   xend = dvs),
               color = "black") +
  labs(title="Intervention effect regression coefficients", y="", x="") +
  ylim(-.5, 1) +
  geom_hline(yintercept=0, color="grey") +
  coord_flip() +
  theme_minimal() +
  theme(aspect.ratio = .3)
```

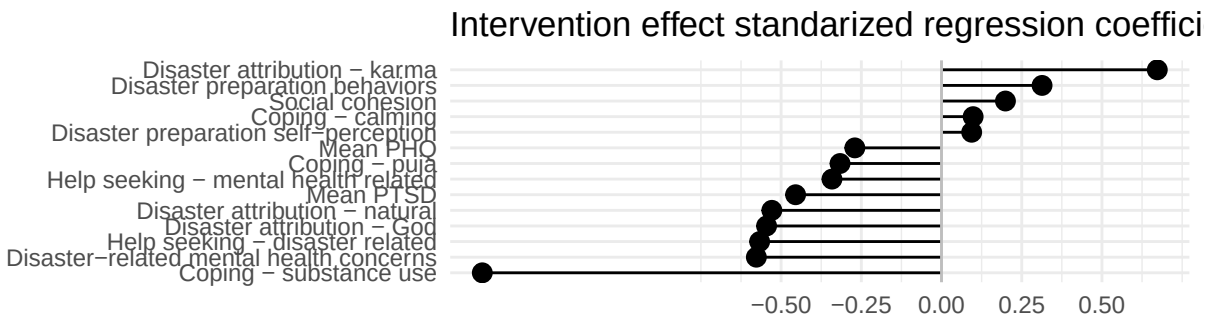


Let's also make a plot of the standarized coefficients (to aid comparison between coefficients derived from dependent variables that are on different scales) by dividing them by the standard deviations of the dependent variables. They're interpreted as a '1 unit increase in intervention effect (i.e., moving from the pre-intervention

phase to the post-intervention phase) is associated with an X standard deviation unit change in the dependent measure, over and above all other effects (e.g., time point, subject-specific intercepts, city effects where applicable).

```
ggplot(effects, aes(x=reorder(dvs, stdestimates), y=stdestimates)) +
  geom_point(stat = "identity", fill = "black", size = 3) +
  geom_segment(aes(y = 0,
                   x = dvs,
                   yend = stdestimates,
                   xend = dvs),
               color = "black") +
  labs(title = "Intervention effect standarized regression coefficients", y="", x="") +

  scale_y_continuous(breaks = seq(-.5, .6, by = .25), expand=expand_scale(add = c(.1, .1))) +
  geom_hline(yintercept = 0, color = "grey") +
  coord_flip() +
  theme_minimal() +
  theme(aspect.ratio = .3)
```




```
  ggsave('std reg coef all.pdf', device=cairo_pdf, width = 7, height = .3*7)
```

Tabular results

Let's also create a table of the results of our models.

```r
dv_names <-
c('Disaster preparation behaviors', 'Mean PHQ', 'Mean PTSD', 'Social cohesion', 'Help seeking - mental h

#models <- list(disPrep, phq, ptsd, soc_coh, help_mental, help_dist, disMH, disAttribNatural, disAttrib
models <- list(disPrepLinear, phq, ptsd, soc_coh, help_mental, help_dist, disMH, disAttribNatural, disA

texreg(models, type = "html",  digits = 3, bold = .05, booktabs = TRUE, sideways = TRUE, use.packages =
```

```r
anovas <- lapply(models, function(x) Anova(x, type = "III"))
```

```
## Warning in update.uC(rho): iteration limit reached when updating the random effects
##   at iteration 286
```

```r
anovas_df <- lapply(anovas, function(x) as.numeric(c(tail(x,1),x['gender',])))
anovas_df <- data.frame(t(sapply(anovas_df, `[`)), row.names = dv_names)
names(anovas_df) <- c('interv.gender.chisq', 'interv.gender.df', 'interv.gender.p', 'gender.chisq', 'ge
anovas_df %<>% select(-gender.df)

mmeans_df <- lapply(models, function(x) as.numeric(summary(pairs(lsmeans::lsmeans(x, ~ gender, at=(list
mmeans_df <-  data.frame(t(sapply(mmeans_df, `[`)), row.names = dv_names)
names(mmeans_df) <- c('Female-Male', 'se', 'df', 't.stat','p.val')

coefs_int <- sapply(models, function(x) coef(summary(x))['interventionTIntervention',1])
se_int <- sapply(models, function(x) coef(summary(x))['interventionTIntervention',2])
p_int <- sapply(models, function(x) coef(summary(x))['interventionTIntervention', ncol(coef(summary(x))
d_int <- vector(mode="numeric", length=length(coefs_int))
for(i in 1:length(coefs_int)){
  if(class(models[[i]]) == "merModLmerTest") {
    y <- getME(models[[i]], name = 'y')
    X <- getME(models[[i]], name = 'X')
    d_int[i] <- coefs_int[i] / sd(y[X[,'timePoint2'] == 0 & X[,'timePoint3'] == 0])
  }
  else {
    d_int[i] <- NA
  }
}
coef_int_df <- data.frame(row.names = dv_names, Coefficient = coefs_int, 'Std error' = se_int, 'P value

coefs_int_gender <- sapply(models, function(x) coef(summary(x))['genderMale:interventionTIntervention',
se_int_gender <- sapply(models, function(x) coef(summary(x))['genderMale:interventionTIntervention',2])
p_int_gender <- sapply(models, function(x) coef(summary(x))['genderMale:interventionTIntervention', nco
d_int_gender <- vector(mode="numeric", length=length(coefs_int_gender))
for(i in 1:length(coefs_int_gender)){
  if(class(models[[i]]) == "merModLmerTest") {
    y <- getME(models[[i]], name = 'y')
    X <- getME(models[[i]], name = 'X')
    d_int_gender[i] <- coefs_int_gender[i] / sd(y[X[,'timePoint2'] == 0 & X[,'timePoint3'] == 0])
  }
  else {
    d_int_gender[i] <- NA
  }
}
coef_int_gender_df <- data.frame(row.names = dv_names, Coefficient = coefs_int_gender, 'Std error' = se
```

	Disaster preparation behaviors	Mean PHQ	Mean PTSD	Social cohesion	Help seeking - mental health	Help seeking - disas
(Constant)	**4.499*****	**1.817*****	**2.065*****	**6.680*****		
	(0.338)	(0.042)	(0.055)	(0.332)		
Time = 2	0.323	**−0.126***	−0.122	−0.213	−0.332	−0.533
	(0.174)	(0.055)	(0.064)	(0.265)	(0.309)	(0.315)
Time = 3	**0.676****	−0.156	−0.106	−0.653	−0.458	−0.723
	(0.259)	(0.081)	(0.095)	(0.394)	(0.441)	(0.449)
Gender (male)	−0.139	**−0.138***	**−0.302*****	0.395	0.263	**0.695***
	(0.191)	(0.070)	(0.092)	(0.280)	(0.339)	(0.342)
Intervention	**0.897*****	**−0.268*****	**−0.275*****	**1.196*****	**0.846***	**1.114****
	(0.223)	(0.069)	(0.081)	(0.338)	(0.377)	(0.384)
Gender (male) x Time = 2	0.362	−0.022	−0.019	0.707	0.676	**1.382****
	(0.277)	(0.089)	(0.104)	(0.422)	(0.512)	(0.528)
Gender (male) x Time = 3	0.453	0.063	0.045	**1.586***	0.605	**1.861***
	(0.416)	(0.135)	(0.159)	(0.630)	(0.747)	(0.757)
Gender (male) x Intervention	−0.392	0.019	0.026	−0.971	−0.305	**−1.359***
	(0.351)	(0.115)	(0.136)	(0.530)	(0.628)	(0.640)
Var: ID:city (Intercept)	0.561			0.958		
Var: city (Intercept)	0.202			0.164		
Var: Residual	1.130	0.115	0.153	2.651		
Var: ID (Intercept)		0.109	0.235			
Variance: ID: (Intercept)					1.472	1.613

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients with $p < 0.05$ in **bold**. Results are presented as coefficient (standard error).

Table 4: Statistical models

	Disaster preparation behaviors	Mean PHQ	Mean PTSD	Social cohesion
(Constant)	**0.621****	**0.774*****	**1.965*****	**6.816*****
	(0.210)	(0.034)	(0.046)	(0.310)
Time point = 2	**0.363*****	**−0.139****	**−0.125***	0.107
	(0.109)	(0.043)	(0.050)	(0.216)
Time point = 3	**0.720*****	**−0.135***	−0.079	−0.052
	(0.196)	(0.065)	(0.076)	(0.328)
Intervention	**0.655*****	**−0.258*****	**−0.274*****	**0.802****
	(0.167)	(0.055)	(0.065)	(0.283)
Var: City (Intercept)	0.077			0.154
Var: Subject (Intercept)	0.399	0.116	0.270	1.036
Var: Residual		0.116	0.152	2.757

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients with $p < 0.05$ in **bold**. Results are presented as coefficient (standard error).

	Disaster preparation behaviors	Mean PHQ	Mean PTSD	Help seeking mental health	Help seeking disaster-related	Social cohesion	Disaster-related mental health	Disaster attribution: natural	Disaster attribution: God	Disaster attribution: karma	Disaster preparation self-perception	Coping: puja	Coping: calming	Coping: substance use	Chronic stressors
(Constant)	**0.621****	**0.774*****	**1.965*****	**2.185*****	**2.429*****	**6.816*****	**4.855*****	**3.220*****	**2.028*****	**1.438*****	**5.956*****	**1.729*****	**1.620*****	**1.262*****	**0.746*****
	(0.210)	(0.034)	(0.046)	(0.068)	(0.118)	(0.310)	(0.115)	(0.069)	(0.243)	(0.061)	(0.082)	(0.133)	(0.058)	(0.037)	(0.059)
Time point = 2	**0.363*****	**−0.139****	**−0.125***	−0.039	−0.063	0.107	−0.033	−0.158	−0.133	0.143	0.206	−0.067	0.045	−0.084	−0.147
	(0.109)	(0.043)	(0.050)	(0.102)	(0.099)	(0.216)	(0.172)	(0.101)	(0.104)	(0.090)	(0.128)	(0.082)	(0.086)	(0.052)	(0.077)
Time point = 3	**0.720*****	**−0.135***	−0.079	−0.127	−0.136	−0.052	−0.160	−0.121	−0.104	**0.326***	**0.449***	−0.129	0.045	−0.081	−0.222
	(0.196)	(0.065)	(0.076)	(0.150)	(0.150)	(0.328)	(0.254)	(0.149)	(0.159)	(0.133)	(0.187)	(0.125)	(0.127)	(0.077)	(0.115)
Intervention	**0.655*****	**−0.258*****	**−0.274*****	**0.332****	**0.367****	**0.802****	−0.336	**0.363****	−0.261	**−0.311****	0.260	0.041	**0.425*****	0.009	−0.032
	(0.167)	(0.055)	(0.065)	(0.127)	(0.130)	(0.283)	(0.214)	(0.126)	(0.137)	(0.113)	(0.157)	(0.108)	(0.107)	(0.065)	(0.098)
Var: City (Intercept)	0.077				0.019	0.154			0.105			0.027			
Var: Subject (Intercept)	0.399	0.116	0.270	0.275	0.286	1.036	0.800	0.312	.673	0.226	0.316	0.466	0.202	0.113	0.335
Var: Residual		0.116	0.152	0.655	0.584	2.757	1.875	0.641	0.635	0.513	1.045	0.394	0.464	0.167	0.362

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients with $p < 0.05$ in **bold**. Results are presented as coefficient (standard error).

```
print(xtable(coef_int_df, auto = TRUE, caption = "Intervention effect coefficients", digits = c(2,2,2,4
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:50:39 2017

	Coefficient	Std.error	P.value	Cohens.d
Disaster preparation behaviors	0.90	0.22	0.0001	0.59
Mean PHQ	-0.27	0.07	0.0001	-0.51
Mean PTSD	-0.28	0.08	0.0008	-0.39
Social cohesion	1.20	0.34	0.0005	0.59
Help seeking - mental health	0.85	0.38	0.0247	
Help seeking - disaster related	1.11	0.38	0.0037	
Disaster-related mental health	-0.27	0.27	0.3054	-0.16
Disaster attribution - natural	1.01	0.42	0.0160	
Disaster attribution - God	-0.49	0.51	0.3297	
Disaster attribution - karma	-1.19	0.51	0.0202	
Disaster preparation self-perception	0.23	0.20	0.2483	0.19
Coping - puja	0.04	0.48	0.9353	
Coping - calming	1.34	0.39	0.0007	
Coping - substance use	0.61	0.99	0.5340	

Table 5: Intervention effect coefficients

```
print(xtable(coef_int_gender_df, auto = TRUE, caption = "Intervention x gender effect coefficients", di
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:50:39 2017

	Coefficient	Std.error	P.value	Cohens.d
Disaster preparation behaviors	-0.39	0.35	0.2651	-0.26
Mean PHQ	0.02	0.12	0.8727	0.04
Mean PTSD	0.03	0.14	0.8497	0.04
Social cohesion	-0.97	0.53	0.0672	-0.48
Help seeking - mental health	-0.31	0.63	0.6266	
Help seeking - disaster related	-1.36	0.64	0.0337	
Disaster-related mental health	-0.18	0.44	0.6838	-0.10
Disaster attribution - natural	0.49	0.82	0.5478	
Disaster attribution - God	-0.14	0.90	0.8732	
Disaster attribution - karma	-0.06	1.10	0.9537	
Disaster preparation self-perception	-0.01	0.33	0.9714	-0.01
Coping - puja	-0.72	0.80	0.3706	
Coping - calming	0.09	0.65	0.8854	
Coping - substance use	-1.06	1.36	0.4360	

Table 6: Intervention x gender effect coefficients

```
contrasts <- data.frame()
for(mod in models) {
  MM <- lsmeans::lsmeans(mod, ~ timePoint * interventionT)
  contrast_result <- summary(rbind(contrast(MM, method = "pairwise")), adjust = "none")
  contrast_result <- contrast_result[nrow(contrast_result) -1, ]
  if(dim(contrasts)[1] == 0) {
    contrasts <- contrast_result
  }
  else {
    contrasts <- rbind(contrasts, setNames(contrast_result, names(contrasts)))
  }
```

```
}
row.names(contrasts) <- dv_names
```

```
print(xtable(mmeans_df, "Marginal contrasts for females - males at time 1", auto = TRUE, digits = c(2,2
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:50:48 2017

	Female-Male	se	df	t.stat	p.val
Disaster preparation behaviors	0.14	0.19	485	0.73	0.4668
Mean PHQ	0.14	0.07	403	1.98	0.0485
Mean PTSD	0.30	0.09	343	3.29	0.0011
Social cohesion	-0.39	0.28	517	-1.41	0.1585
Help seeking - mental health	-0.26	0.34		-0.78	0.4367
Help seeking - disaster related	-0.69	0.34		-2.03	0.0423
Disaster-related mental health	0.95	0.23	520	4.07	0.0001
Disaster attribution - natural	-0.89	0.42		-2.13	0.0335
Disaster attribution - God	2.06	0.50		4.16	0.0000
Disaster attribution - karma	1.45	0.57		2.56	0.0104
Disaster preparation self-perception	-0.11	0.17	534	-0.66	0.5117
Coping - puja	0.64	0.52		1.23	0.2175
Coping - calming	0.24	0.36		0.67	0.5044
Coping - substance use	-2.40	0.91		-2.62	0.0088

Table 7: Marginal contrasts for females - males at time 1

```
print(xtable(anovas_df, "ANOVA results for intervention x gender and gender main effects", auto = TRUE,
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:50:48 2017

	interv.gender.chisq	interv.gender.df	interv.gender.p	gender.chisq	gender.p
Disaster preparation behaviors	1.24	1	0.2646	0.53	0.4664
Mean PHQ	0.03	1	0.8726	3.92	0.0478
Mean PTSD	0.04	1	0.8496	10.83	0.0010
Social cohesion	3.36	1	0.0667	1.99	0.1579
Help seeking - mental health	0.24	1	0.6265	-0.00	1.0000
Help seeking - disaster related	4.52	1	0.0334	-0.00	1.0000
Disaster-related mental health	0.17	1	0.6837	16.56	0.0000
Disaster attribution - natural	0.36	1	0.5458	-0.00	1.0000
Disaster attribution - God	-0.00	1	1.0000	-0.03	1.0000
Disaster attribution - karma	0.00	1	0.9536	-0.00	1.0000
Disaster preparation self-perception	0.00	1	0.9714	0.43	0.5115
Coping - puja	0.81	1	0.3694	0.00	0.9999
Coping - calming	0.02	1	0.8853	-0.00	1.0000
Coping - substance use	0.62	1	0.4317	0.00	1.0000

Table 8: ANOVA results for intervention x gender and gender main effects

```
print(xtable(cbind(dv_names, contrasts)[,2:ncol(contrasts)+1], auto = TRUE, caption = "Within subject c
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:50:48 2017

Finally we'll output some descriptive statistics. First for the mental health variables

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Mon Oct 23 14:47:35 2017

Variable	**Time point**	**n**	**Min**	$\mathbf{q_1}$	$\mathbf{\tilde{x}}$	$\mathbf{\bar{x}}$	$\mathbf{q_3}$	**Max**

PHQ	1	202	1	1.33	1.67	1.77	2.11	3.44
	2	201	1	1.11	1.33	1.51	1.78	3.33
	3	202	1	1.11	1.33	1.38	1.56	3.22
	all		1	1.11	1.44	1.55	1.89	3.44
PTSD	1	202	1	1.41	1.88	1.96	2.35	4.53
	2	201	1	1.24	1.53	1.71	1.94	4.53
	3	202	1	1.18	1.47	1.61	1.94	3.88
	all		1	1.24	1.59	1.76	2.12	4.53
Dis MH - anxious dep	1	202	1	2.00	2.00	2.57	3.75	5.00
	2	201	1	2.00	2.00	2.33	3.00	5.00
	3	202	1	2.00	2.00	2.18	3.00	5.00
	all		1	2.00	2.00	2.36	3.00	5.00
Dis MH - avoid	1	202	1	2.00	2.00	2.27	3.00	5.00
	2	201	1	2.00	2.00	2.32	3.00	5.00
	3	202	1	1.00	2.00	2.19	3.00	5.00
	all		1	2.00	2.00	2.26	3.00	5.00

Table 10: Descriptive statistics

Then also for the qualitative data regarding new trauma experiences.

```
qualitative_data <- filtered %>% filter(timePoint == "3") %>% select(T3NewTrauma, T3NewTraumaopen)
tableNominal(vars = as.data.frame(qualitative_data), cumsum = FALSE, longtable = TRUE)
```

% latex table generated in R 3.4.2 by xtable 1.8-2 package % Wed Nov 15 13:50:48 2017

Variable	**Levels**	**n**	%
T3NewTrauma	0	194	96.0
	1	8	4.0
	all	202	100.0
T3NewTraumaopen	0	195	96.1
	aja bholi srimati lai dindinai behosh bhai raheko xa yo 14 dinma 5,6 patak behosh bhaisakyo .	1	0.5
	baccha chadeko gadi palteko	1	0.5
	birami bhaye	1	0.5
	birami ko karan le	1	0.5
	chhorako bahira padna gani kurama	1	0.5
	gharayasi ghatanale	1	0.5
	ghareru samasyaharu	1	0.5
	srimanlai kukurle toker afulai akdamai tanab bhayeko.	1	0.5
	all	203	100.0

Table 11:

	estimate	SE	df	t.ratio	p.value
Disaster preparation behaviors	-0.90	0.22	400.87	-4.09	0.000
Mean PHQ	0.12	0.07	462.59	1.83	0.068
Mean PTSD	0.08	0.08	442.83	1.05	0.293
Social cohesion	-0.14	0.34	371.79	-0.42	0.678
Help seeking - mental health	0.16	0.37		0.42	0.675
Help seeking - disaster related	-0.21	0.38		-0.55	0.583
Disaster-related mental health	0.13	0.26	505.88	0.51	0.611
Disaster attribution - natural	0.31	0.48		0.65	0.515
Disaster attribution - God	0.56	0.53		1.07	0.286
Disaster attribution - karma	-1.42	0.64		-2.22	0.026
Disaster preparation self-perception	-0.48	0.20	512.45	-2.43	0.015
Coping - puja	-0.20	0.47		-0.42	0.677
Coping - calming	-0.09	0.39		-0.22	0.827
Coping - substance use	1.18	0.82		1.44	0.149

Table 9: Within subject contrasts for time 1 to time 3 for intervention group