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)
library(tidyr)
library(Hmisc)
library(PerformanceAnalytics)
```

```r
library(SWSamp)
library(sjstats)
#source("https://raw.github.com/glmmTMB/glmmTMB/master/misc/lsmeans.R")
```

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). We also need a variable containing initial randomization to treatment (which is based upon the city of the participant because of the cluster randomization design) - this will be used for any intent-to-treat analyses (our regular `interventionT` variable has missing data for some subjects who did not have any followup data because we want to exclude that data from our main as-treated analyses).

```r
setwd("C:/Users/ajame/Dropbox/Alex - Nepal/EQ data")
data <- read_dta("Kathmandu_Valley_NEPAL_all_times WITH LABELS reshaped.dta")
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$initialRandomization <- 0
data$initialRandomization[data$city=="Chhaling" & data$timePoint == "2"] <- 1
data$initialRandomization[data$timePoint == "3"] <- 1
data$initialRandomization <- factor(data$initialRandomization, labels = c('Control', 'Intervention'))
data$phqMean6_T <- data$phqMean6_T + 1
data %<>% mutate(EQTrauma_fixed = select(., starts_with("T1Trauma"), -contains("assault"), -ends_with("
data %<>% mutate(disPrepBehaviorsExcludedItems_T1 = select(. , T1Disprep3Foodwater, T1Disprep3Dwelling,
                 disPrepBehaviorsExcludedItems_T2 = select(. , T2Disprep3Foodwater, T2Disprep3Dwelling,
                 disPrepBehaviorsExcludedItems_T3 = select(. , T3Disprep3Foodwater, T3Disprep3Dwelling,

data[['disPrepBehaviorsExcludedItems_T']] <- melt_data_suffix('disPrepBehaviorsExcludedItems_T')

to_melt_prefix <- c('T1DisMH1Anxiousdep', 'T1DisMH2Avoid', 'T1Dem4bReligtime')

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)
#write_dta(filtered, 'C:/Users/ajame/Dropbox/Alex - Nepal/EQ data/filtered_fixed_trauma.dta', version =
```

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

```r
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
```

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

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:28:52 2018

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 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:28:52 2018

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 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:28:53 2018

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
```

```r
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
```

Now we'll get alpha values for our *entire sample* at time 1 to assess the quality of the mental health and behavioral scales used in the survery.

```
psych::alpha(data %>% filter(timePoint == "1") %>% select(starts_with("T1Hes")))
```

```
##
## Reliability analysis
## Call: psych::alpha(x = data %>% filter(timePoint == "1") %>% select(starts_with("T1Hes")))
##
##   raw_alpha std.alpha G6(smc) average_r  S/N   ase mean  sd
##       0.49      0.49     0.4      0.24 0.97 0.057 0.25 0.3
##
##  lower alpha upper     95% confidence boundaries
## 0.38 0.49 0.6
##
##  Reliability if an item is dropped:
##                  raw_alpha std.alpha G6(smc) average_r  S/N alpha se
## T1Hes1Waterfood      0.47      0.47    0.31      0.31 0.89    0.068
## T1Hes2Health         0.39      0.39    0.24      0.24 0.63    0.079
## T1Hes3Income         0.31      0.31    0.19      0.19 0.45    0.088
##
##  Item statistics
##                   n raw.r std.r r.cor r.drop mean   sd
## T1Hes1Waterfood 239  0.70  0.67  0.37   0.27 0.30 0.46
## T1Hes2Health    239  0.66  0.71  0.45   0.31 0.17 0.38
## T1Hes3Income    239  0.75  0.73  0.51   0.35 0.28 0.45
##
## Non missing response frequency for each item
##                    0    1 miss
## T1Hes1Waterfood 0.70 0.30    0
## T1Hes2Health    0.83 0.17    0
## T1Hes3Income    0.72 0.28    0
```

```
psych::alpha(data %>% filter(timePoint == "1") %>% select(starts_with("T1Trauma"), -contains("assault")
```

```
## Warning in psych::alpha(data %>% filter(timePoint == "1") %>%
## select(starts_with("T1Trauma"), : Item = T1Trauma1EQ had no variance and
## was deleted
```

```
##
## Reliability analysis
## Call: psych::alpha(x = data %>% filter(timePoint == "1") %>% select(starts_with("T1Trauma"),
##     -contains("assault"), -ends_with("open"), -T1Trauma2bWheresleeping))
```

```
##
##   raw_alpha std.alpha G6(smc) average_r  S/N   ase mean   sd
##       0.37      0.37    0.36       0.1 0.58 0.063 0.27 0.16
##
##  lower alpha upper     95% confidence boundaries
## 0.24 0.37 0.49
##
##  Reliability if an item is dropped:
##                     raw_alpha std.alpha G6(smc) average_r  S/N alpha se
## T1Trauma2aHousedest      0.42      0.43    0.40     0.157 0.74    0.060
## T1Trauma3Rubble          0.26      0.25    0.26     0.077 0.33    0.075
## T1Trauma4Injured         0.17      0.15    0.15     0.043 0.18    0.085
## T1Trauma5Faminjury       0.19      0.20    0.21     0.059 0.25    0.086
## T1Trauma6Famkilled       0.46      0.47    0.42     0.181 0.88    0.056
##
##  Item statistics
##                       n raw.r std.r  r.cor  r.drop  mean   sd
## T1Trauma2aHousedest 239  0.39  0.41  0.081  0.0378 0.912 0.28
## T1Trauma3Rubble     239  0.57  0.59  0.421  0.2491 0.092 0.29
## T1Trauma4Injured    238  0.64  0.67  0.604  0.3790 0.071 0.26
## T1Trauma5Faminjury  239  0.69  0.63  0.512  0.3046 0.163 0.37
## T1Trauma6Famkilled  239  0.36  0.36 -0.011 -0.0093 0.096 0.30
##
## Non missing response frequency for each item
##                        0    1 miss
## T1Trauma2aHousedest 0.09 0.91 0.00
## T1Trauma3Rubble     0.91 0.09 0.00
## T1Trauma4Injured    0.93 0.07 0.01
## T1Trauma5Faminjury  0.84 0.16 0.00
## T1Trauma6Famkilled  0.90 0.10 0.00
```

```r
psych::alpha(data %>% filter(timePoint == "1") %>% select(T1Disprep3Supplykit, T1Disprep3Foodwater, T1Di
```

```
##
## Reliability analysis
## Call: psych::alpha(x = data %>% filter(timePoint == "1") %>% select(T1Disprep3Supplykit,
##     T1Disprep3Foodwater, T1Disprep3Docs, T1Disprep3Dwelling,
##     T1Disprep3Furn, T1Disprep3Famplan, T1Disprep3Commplan), cumulative = TRUE)
##
##   raw_alpha std.alpha G6(smc) average_r S/N  ase mean  sd
##       0.59       0.6     0.6      0.18 1.5 0.04  4.5 1.6
##
##  lower alpha upper     95% confidence boundaries
## 0.51 0.59 0.67
##
##  Reliability if an item is dropped:
##                     raw_alpha std.alpha G6(smc) average_r S/N alpha se
## T1Disprep3Supplykit      0.59      0.61    0.60      0.21 1.6    0.041
## T1Disprep3Foodwater      0.52      0.54    0.54      0.16 1.2    0.048
## T1Disprep3Docs           0.53      0.54    0.53      0.16 1.2    0.046
## T1Disprep3Dwelling       0.52      0.53    0.52      0.16 1.1    0.047
## T1Disprep3Furn           0.54      0.54    0.53      0.17 1.2    0.045
## T1Disprep3Famplan        0.60      0.61    0.58      0.20 1.5    0.038
## T1Disprep3Commplan       0.56      0.58    0.57      0.19 1.4    0.043
##
```

```
##  Item statistics
##                       n raw.r std.r r.cor r.drop mean   sd
## T1Disprep3Supplykit 239  0.38  0.44  0.24   0.19 0.10 0.31
## T1Disprep3Foodwater 239  0.64  0.60  0.49   0.39 0.64 0.48
## T1Disprep3Docs      239  0.57  0.61  0.51   0.39 0.87 0.33
## T1Disprep3Dwelling  239  0.59  0.62  0.54   0.41 0.86 0.35
## T1Disprep3Furn      239  0.60  0.59  0.51   0.35 0.68 0.47
## T1Disprep3Famplan   239  0.50  0.44  0.28   0.20 0.50 0.50
## T1Disprep3Commplan  239  0.50  0.51  0.36   0.29 0.83 0.37
##
## Non missing response frequency for each item
##                        0    1 miss
## T1Disprep3Supplykit 0.90 0.10    0
## T1Disprep3Foodwater 0.36 0.64    0
## T1Disprep3Docs      0.13 0.87    0
## T1Disprep3Dwelling  0.14 0.86    0
## T1Disprep3Furn      0.32 0.68    0
## T1Disprep3Famplan   0.50 0.50    0
## T1Disprep3Commplan  0.17 0.83    0
```

```r
psych::alpha(data %>% filter(timePoint == "1") %>% select(starts_with("T1PHQ"), -T1PHQ10Functioning))
```

```
##
## Reliability analysis
## Call: psych::alpha(x = data %>% filter(timePoint == "1") %>% select(starts_with("T1PHQ"),
##     -T1PHQ10Functioning))
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
##       0.81      0.81    0.81      0.32 4.3 0.017 0.75 0.52
##
##  lower alpha upper     95% confidence boundaries
## 0.78 0.81 0.85
##
##  Reliability if an item is dropped:
##                           raw_alpha std.alpha G6(smc) average_r S/N
## T1PHQ1Littleinterest           0.81      0.80    0.80      0.34 4.1
## T1PHQ2Depressed                0.77      0.77    0.76      0.30 3.4
## T1PHQ3Troublesleeping          0.79      0.79    0.79      0.32 3.7
## T1PHQ4Tired                    0.79      0.79    0.78      0.31 3.7
## T1PHQ5Poorappetite             0.80      0.79    0.79      0.32 3.8
## T1PHQ6Feelingbadaboutself      0.79      0.79    0.78      0.32 3.7
## T1PHQ7Troubleconcentrating     0.78      0.78    0.77      0.30 3.5
## T1PHQ8Movingspeakingslowly     0.81      0.80    0.80      0.34 4.1
## T1PHQ9Suicidal                 0.81      0.81    0.81      0.35 4.3
##                           alpha se
## T1PHQ1Littleinterest         0.018
## T1PHQ2Depressed              0.022
## T1PHQ3Troublesleeping        0.020
## T1PHQ4Tired                  0.020
## T1PHQ5Poorappetite           0.019
## T1PHQ6Feelingbadaboutself    0.019
## T1PHQ7Troubleconcentrating   0.020
## T1PHQ8Movingspeakingslowly   0.018
## T1PHQ9Suicidal               0.018
##
```

```
##  Item statistics
##                              n raw.r std.r r.cor r.drop mean   sd
## T1PHQ1Littleinterest       239  0.58  0.55  0.46   0.43 1.02 0.89
## T1PHQ2Depressed            238  0.77  0.76  0.75   0.67 1.15 0.91
## T1PHQ3Troublesleeping      239  0.67  0.64  0.59   0.53 0.86 0.95
## T1PHQ4Tired                239  0.68  0.67  0.63   0.57 1.15 0.83
## T1PHQ5Poorappetite         238  0.63  0.62  0.55   0.50 0.68 0.83
## T1PHQ6Feelingbadaboutself  237  0.64  0.65  0.60   0.52 0.49 0.78
## T1PHQ7Troubleconcentrating 239  0.72  0.72  0.68   0.61 0.85 0.87
## T1PHQ8Movingspeakingslowly 239  0.53  0.55  0.46   0.40 0.35 0.71
## T1PHQ9Suicidal             239  0.45  0.50  0.39   0.35 0.20 0.56
##
## Non missing response frequency for each item
##                               0    1    2    3 miss
## T1PHQ1Littleinterest       0.32 0.40 0.22 0.06 0.00
## T1PHQ2Depressed            0.26 0.41 0.24 0.09 0.01
## T1PHQ3Troublesleeping      0.47 0.26 0.21 0.06 0.00
## T1PHQ4Tired                0.22 0.47 0.25 0.06 0.00
## T1PHQ5Poorappetite         0.53 0.29 0.16 0.03 0.01
## T1PHQ6Feelingbadaboutself  0.65 0.24 0.08 0.03 0.01
## T1PHQ7Troubleconcentrating 0.42 0.36 0.18 0.05 0.00
## T1PHQ8Movingspeakingslowly 0.76 0.16 0.06 0.03 0.00
## T1PHQ9Suicidal             0.87 0.09 0.03 0.02 0.00
```

```
psych::alpha(data %>% filter(timePoint == "1") %>% select(starts_with("T1PTSD"), -ends_with("open"), -T
```

```
##
## Reliability analysis
## Call: psych::alpha(x = data %>% filter(timePoint == "1") %>% select(starts_with("T1PTSD"),
##     -ends_with("open"), -T1PTSDincidentEQrelated))
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean   sd
##       0.89      0.89    0.91      0.33 8.3 0.0098  1.9 0.69
##
##  lower alpha upper     95% confidence boundaries
## 0.87 0.89 0.91
##
##  Reliability if an item is dropped:
##                                 raw_alpha std.alpha G6(smc) average_r S/N
## T1PTSD1Memories                      0.88      0.88    0.90      0.32 7.5
## T1PTSD2Dreams                        0.89      0.89    0.90      0.33 7.8
## T1PTSD3Flashbacks                    0.89      0.89    0.90      0.33 7.8
## T1PTSD4Upsetfromreminders            0.88      0.88    0.90      0.32 7.5
## T1PTSD5Physreactionstoreminders      0.89      0.88    0.90      0.32 7.6
## T1PTSD6Avoidthinkingtalking          0.89      0.89    0.91      0.34 8.2
## T1PTSD7Avoidactivitiessit            0.89      0.89    0.90      0.34 8.1
## T1PTSD8Diffremembertrauma            0.90      0.90    0.91      0.35 8.6
## T1PTSD9Diffenjoyingactiv             0.89      0.88    0.90      0.32 7.7
## T1PTSD10Distantfromothers            0.89      0.89    0.90      0.33 7.8
## T1PTSD11Emotnumb                     0.89      0.88    0.90      0.32 7.7
## T1PTSD12Darkfuture                   0.88      0.88    0.90      0.32 7.5
## T1PTSD13Sleep                        0.89      0.89    0.90      0.33 7.9
## T1PTSD14Anger                        0.89      0.89    0.90      0.34 8.1
## T1PTSD15Concent                      0.89      0.89    0.90      0.33 7.8
## T1PTSD16Suspicionhypervig            0.88      0.88    0.90      0.32 7.5
```

```
## T1PTSD17Easilystartled               0.89      0.89    0.90      0.33 7.7
##                                  alpha se
## T1PTSD1Memories                    0.0107
## T1PTSD2Dreams                      0.0103
## T1PTSD3Flashbacks                  0.0103
## T1PTSD4Upsetfromreminders          0.0108
## T1PTSD5Physreactionstoreminders    0.0105
## T1PTSD6Avoidthinkingtalking        0.0100
## T1PTSD7Avoidactivitiessit          0.0100
## T1PTSD8Diffremembertrauma          0.0097
## T1PTSD9Diffenjoyingactiv           0.0106
## T1PTSD10Distantfromothers          0.0105
## T1PTSD11Emotnumb                   0.0105
## T1PTSD12Darkfuture                 0.0108
## T1PTSD13Sleep                      0.0103
## T1PTSD14Anger                      0.0100
## T1PTSD15Concent                    0.0104
## T1PTSD16Suspicionhypervig          0.0107
## T1PTSD17Easilystartled             0.0105
##
##  Item statistics
##                                    n raw.r std.r r.cor r.drop mean   sd
## T1PTSD1Memories                  239  0.70  0.70  0.69   0.64  2.3 1.20
## T1PTSD2Dreams                    238  0.58  0.60  0.56   0.53  1.6 0.95
## T1PTSD3Flashbacks                239  0.61  0.61  0.58   0.54  2.4 1.25
## T1PTSD4Upsetfromreminders        239  0.73  0.72  0.71   0.67  2.2 1.22
## T1PTSD5Physreactionstoreminders 239  0.66  0.66  0.64   0.60  1.8 1.09
## T1PTSD6Avoidthinkingtalking      237  0.47  0.49  0.44   0.41  1.6 0.89
## T1PTSD7Avoidactivitiessit        238  0.49  0.50  0.46   0.42  1.6 1.05
## T1PTSD8Diffremembertrauma        239  0.36  0.37  0.31   0.28  1.6 1.00
## T1PTSD9Diffenjoyingactiv         237  0.65  0.65  0.63   0.60  1.9 1.16
## T1PTSD10Distantfromothers        238  0.63  0.62  0.59   0.56  1.9 1.20
## T1PTSD11Emotnumb                 239  0.64  0.64  0.62   0.59  1.6 1.07
## T1PTSD12Darkfuture               238  0.71  0.70  0.68   0.64  2.3 1.37
## T1PTSD13Sleep                    238  0.58  0.58  0.55   0.51  1.8 1.07
## T1PTSD14Anger                    236  0.53  0.51  0.47   0.44  2.1 1.26
## T1PTSD15Concent                  237  0.62  0.62  0.59   0.56  1.8 1.10
## T1PTSD16Suspicionhypervig        238  0.70  0.70  0.68   0.64  2.4 1.21
## T1PTSD17Easilystartled           239  0.63  0.64  0.62   0.58  1.7 1.02
##
## Non missing response frequency for each item
##                                    0    1    2    3    4    5 miss
## T1PTSD1Memories                 0.00 0.32 0.33 0.17 0.13 0.06 0.00
## T1PTSD2Dreams                   0.00 0.68 0.15 0.11 0.05 0.01 0.01
## T1PTSD3Flashbacks               0.00 0.32 0.26 0.18 0.19 0.05 0.00
## T1PTSD4Upsetfromreminders       0.00 0.38 0.27 0.16 0.14 0.05 0.00
## T1PTSD5Physreactionstoreminders 0.00 0.58 0.20 0.12 0.08 0.03 0.00
## T1PTSD6Avoidthinkingtalking     0.00 0.59 0.27 0.09 0.03 0.02 0.01
## T1PTSD7Avoidactivitiessit       0.00 0.68 0.15 0.10 0.03 0.04 0.01
## T1PTSD8Diffremembertrauma       0.00 0.65 0.15 0.11 0.08 0.01 0.00
## T1PTSD9Diffenjoyingactiv        0.00 0.50 0.22 0.15 0.10 0.03 0.01
## T1PTSD10Distantfromothers       0.00 0.58 0.17 0.12 0.08 0.05 0.01
## T1PTSD11Emotnumb                0.00 0.67 0.17 0.06 0.06 0.03 0.00
## T1PTSD12Darkfuture              0.00 0.43 0.19 0.16 0.13 0.09 0.01
```

```
## T1PTSD13Sleep                    0.00 0.53 0.23 0.14 0.08 0.02 0.01
## T1PTSD14Anger                    0.00 0.42 0.25 0.15 0.11 0.06 0.02
## T1PTSD15Concent                  0.00 0.55 0.22 0.14 0.07 0.03 0.01
## T1PTSD16Suspicionhypervig        0.00 0.29 0.34 0.17 0.14 0.06 0.01
## T1PTSD17Easilystartled           0.01 0.59 0.22 0.10 0.06 0.02 0.00
```

```r
psych::alpha(data %>% filter(timePoint == "1") %>% select(T1SocCoh1Helpneighbors, T1SocCoh2Dontgetalong
```

```
##
## Reliability analysis
## Call: psych::alpha(x = data %>% filter(timePoint == "1") %>% select(T1SocCoh1Helpneighbors,
##     T1SocCoh2DontgetalongrevCoded))
##
##   raw_alpha std.alpha G6(smc) average_r  S/N   ase mean sd
##        0.4      0.41    0.25      0.25 0.68 0.076  3.4  1
##
##  lower alpha upper     95% confidence boundaries
## 0.25 0.4 0.55
##
##  Reliability if an item is dropped:
##                               raw_alpha std.alpha G6(smc) average_r S/N
## T1SocCoh1Helpneighbors             0.25      0.25   0.065      0.25  NA
## T1SocCoh2DontgetalongrevCoded      0.25      0.25   0.065      0.25  NA
##                               alpha se
## T1SocCoh1Helpneighbors              NA
## T1SocCoh2DontgetalongrevCoded       NA
##
##  Item statistics
##                                 n raw.r std.r r.cor r.drop mean  sd
## T1SocCoh1Helpneighbors        238  0.84  0.79   0.4   0.25  3.5 1.4
## T1SocCoh2DontgetalongrevCoded 238  0.74  0.79   0.4   0.25  3.3 1.1
##
## Non missing response frequency for each item
##                                  1    2    3    4    5 miss
## T1SocCoh1Helpneighbors        0.16 0.05 0.25 0.19 0.34 0.01
## T1SocCoh2DontgetalongrevCoded 0.10 0.06 0.45 0.20 0.19 0.01
```

We also want to examine test-retest reliability for our various scales by doing a simple Pearson correlation from time 1 to time 2 in untreated subjects (Tathali community). We have to restructure our data using `tidyr::spread` to get it in the proper wide format.

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(chronicS
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 5.6948, df = 111, p-value = 1.025e-07
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.3187817 0.6069264
## sample estimates:
##       cor
## 0.4755095
```

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(disPrepBe
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 2.2865, df = 111, p-value = 0.02413
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.02846913 0.38185311
## sample estimates:
##       cor
## 0.2120836
```

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(phqMean6
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 6.604, df = 111, p-value = 1.433e-09
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.3840603 0.6518819
## sample estimates:
##       cor
## 0.5311093
```

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(ptsdMean
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 10.664, df = 111, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.6063023 0.7920109
## sample estimates:
##       cor
## 0.7113585
```

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(socialCo
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 3.8984, df = 111, p-value = 0.0001661
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.1734116 0.4997196
## sample estimates:
##       cor
## 0.3470247
```

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(HelpSeeki
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 3.8616, df = 111, p-value = 0.0001897
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.1702354 0.4972601
## sample estimates:
##       cor
## 0.3441428
```

```r
cor.test( ~ `1` + `2`, data = data %>% filter(timePoint != "3" & city == "Tathali") %>% select(HelpSeeki
```

```
##
##  Pearson's product-moment correlation
##
## data:  1 and 2
## t = 2.1285, df = 111, p-value = 0.03551
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.01379932 0.36924675
## sample estimates:
##       cor
## 0.1980243
```

```r
# the following two questions are simply yes or no questions, and we will measure test-retest reliabili
data %>% filter(timePoint != "3" & city == "Tathali") %>% summarise(concordance1_help_mental = mean(Help
```

```
## # A tibble: 1 x 1
##   concordance1_help_mental
##                      <dbl>
## 1                    0.947
```

```r
data %>% filter(timePoint != "3" & city == "Tathali") %>% summarise(concordance1_help_dis = mean(HelpGiv
```

```
## # A tibble: 1 x 1
##   concordance1_help_dis
##                   <dbl>
## 1                 0.965
```

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

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and phqMean6_T
## t = -2.2525, df = 237, p-value = 0.0252
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.26676992 -0.01821542
## sample estimates:
```

```
##        cor
## -0.1447758
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and ptsdMean11_T
## t = -0.86251, df = 237, p-value = 0.3893
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.18154445  0.07146422
## sample estimates:
##         cor
## -0.05593808
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and socialCohesionT
## t = 2.2293, df = 236, p-value = 0.02673
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.0167582 0.2659195
## sample estimates:
##      cor
## 0.143614
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and HelpSeekingMentalT
## t = 0.01974, df = 236, p-value = 0.9843
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1258974  0.1284258
## sample estimates:
##        cor
## 0.00128499
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and HelpSeekingDisT
## t = 1.32, df = 236, p-value = 0.1881
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.04201089  0.21047878
## sample estimates:
##        cor
```

```
## 0.08560826
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and copingPuja_T
## t = 0.17993, df = 236, p-value = 0.8574
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1156222  0.1386672
## sample estimates:
##        cor
## 0.01171186
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and copingCalming_T
## t = 3.7452, df = 235, p-value = 0.0002267
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.1133298 0.3540551
## sample estimates:
##       cor
## 0.2373326
```

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

```
##
##  Pearson's product-moment correlation
##
## data:  disPrepBehaviorsT and copingSubuse_T
## t = -0.68465, df = 235, p-value = 0.4942
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.17107479  0.08328667
## sample estimates:
##         cor
## -0.04461715
```

```r
rcorr(as.matrix(data %>% filter(timePoint == "1") %>% select(disPrepBehaviorsT, phqMean6_T, ptsdMean11_
```

```
##                      disPrepBehaviorsT phqMean6_T ptsdMean11_T
## disPrepBehaviorsT                 1.00      -0.14        -0.06
## phqMean6_T                       -0.14       1.00         0.73
## ptsdMean11_T                     -0.06       0.73         1.00
## socialCohesionT                   0.14      -0.22        -0.22
## HelpSeekingMentalT                0.00       0.01         0.04
## HelpSeekingDisT                   0.09      -0.15        -0.07
##                      socialCohesionT HelpSeekingMentalT HelpSeekingDisT
## disPrepBehaviorsT               0.14               0.00            0.09
## phqMean6_T                     -0.22               0.01           -0.15
## ptsdMean11_T                   -0.22               0.04           -0.07
```

```
## socialCohesionT              1.00              0.17            0.19
## HelpSeekingMentalT           0.17              1.00            0.55
## HelpSeekingDisT              0.19              0.55            1.00
##
## n
##                    disPrepBehaviorsT phqMean6_T ptsdMean11_T
## disPrepBehaviorsT                239        239          239
## phqMean6_T                       239        239          239
## ptsdMean11_T                     239        239          239
## socialCohesionT                  238        238          238
## HelpSeekingMentalT               238        238          238
## HelpSeekingDisT                  238        238          238
##                    socialCohesionT HelpSeekingMentalT HelpSeekingDisT
## disPrepBehaviorsT              238                238             238
## phqMean6_T                     238                238             238
## ptsdMean11_T                   238                238             238
## socialCohesionT                238                238             238
## HelpSeekingMentalT             238                238             238
## HelpSeekingDisT                238                238             238
##
## P
##                    disPrepBehaviorsT phqMean6_T ptsdMean11_T
## disPrepBehaviorsT                    0.0252     0.3893
## phqMean6_T         0.0252                       0.0000
## ptsdMean11_T       0.3893            0.0000
## socialCohesionT    0.0267            0.0008     0.0007
## HelpSeekingMentalT 0.9843            0.8507     0.5250
## HelpSeekingDisT    0.1881            0.0175     0.2499
##                    socialCohesionT HelpSeekingMentalT HelpSeekingDisT
## disPrepBehaviorsT  0.0267          0.9843             0.1881
## phqMean6_T         0.0008          0.8507             0.0175
## ptsdMean11_T       0.0007          0.5250             0.2499
## socialCohesionT                    0.0097             0.0029
## HelpSeekingMentalT 0.0097                             0.0000
## HelpSeekingDisT    0.0029          0.0000
```

```r
chart.Correlation(data %>% filter(timePoint == "1") %>% select(disPrepBehaviorsT, phqMean6_T, ptsdMean1
```

```
## Warning in plot.window(...): "method" is not a graphical parameter

## Warning in plot.xy(xy, type, ...): "method" is not a graphical parameter

## Warning in title(...): "method" is not a graphical parameter

## Warning in plot.window(...): "method" is not a graphical parameter

## Warning in plot.xy(xy, type, ...): "method" is not a graphical parameter

## Warning in title(...): "method" is not a graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "method" is
## not a graphical parameter

## Warning in plot.window(...): "method" is not a graphical parameter

## Warning in plot.xy(xy, type, ...): "method" is not a graphical parameter

## Warning in title(...): "method" is not a graphical parameter

## Warning in plot.window(...): "method" is not a graphical parameter
```

```
## Warning in plot.xy(xy, type, ...): "method" is not a graphical parameter
## Warning in title(...): "method" is not a graphical parameter
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```
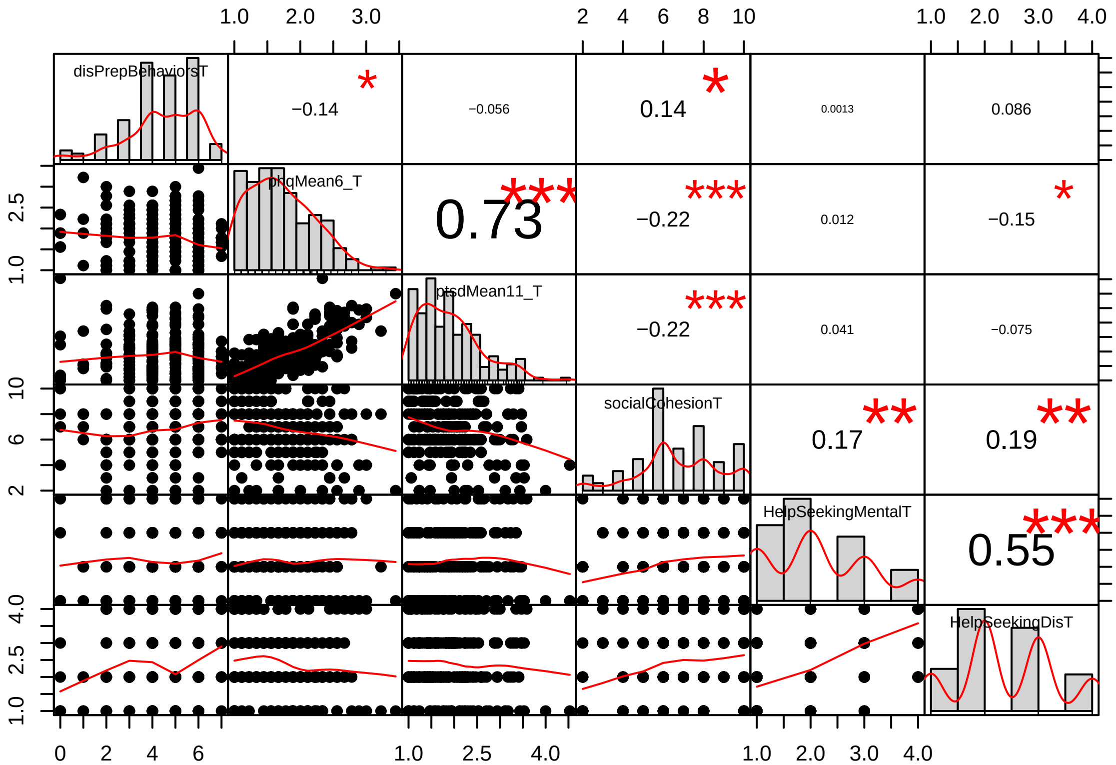



Let's also look at some gender differences at baseline.

```r
t.test(disPrepBehaviorsT ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  disPrepBehaviorsT by gender
## t = -0.31793, df = 236, p-value = 0.7508
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.4661761  0.3366214
## sample estimates:
## mean in group Female   mean in group Male
##             4.461538             4.526316
```

```r
t.test(phqMean6_T ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE )
```

```
##
##  Two Sample t-test
##
## data:  phqMean6_T by gender
## t = 2.954, df = 236, p-value = 0.003454
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.06673597 0.33397969
## sample estimates:
## mean in group Female   mean in group Male
```

```
##              1.828574             1.628216
```

```r
t.test(ptsdMean11_T ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE )
```

```
##
##  Two Sample t-test
##
## data:  ptsdMean11_T by gender
## t = 4.0234, df = 236, p-value = 7.727e-05
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.1818794 0.5308817
## sample estimates:
## mean in group Female   mean in group Male
##             2.056535             1.700155
```

```r
t.test(socialCohesionT ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  socialCohesionT by gender
## t = -1.6672, df = 235, p-value = 0.09681
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.98265426  0.08183884
## sample estimates:
## mean in group Female   mean in group Male
##             6.633803             7.084211
```

```r
t.test(HelpSeekingMentalT ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  HelpSeekingMentalT by gender
## t = -0.59565, df = 235, p-value = 0.552
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.3301672  0.1768685
## sample estimates:
## mean in group Female   mean in group Male
##             2.154930             2.231579
```

```r
t.test(HelpSeekingDisT ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  HelpSeekingDisT by gender
## t = -1.9855, df = 235, p-value = 0.04825
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.479966311 -0.001872088
## sample estimates:
## mean in group Female   mean in group Male
##             2.338028             2.578947
```

```r
t.test(copingPuja_T ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  copingPuja_T by gender
## t = 1.0178, df = 235, p-value = 0.3098
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.1273529  0.3995545
## sample estimates:
## mean in group Female   mean in group Male
##             1.788732             1.652632
```

```r
t.test(copingCalming_T ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  copingCalming_T by gender
## t = 1.2326, df = 234, p-value = 0.219
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.08409697  0.36518777
## sample estimates:
## mean in group Female   mean in group Male
##             1.683099             1.542553
```

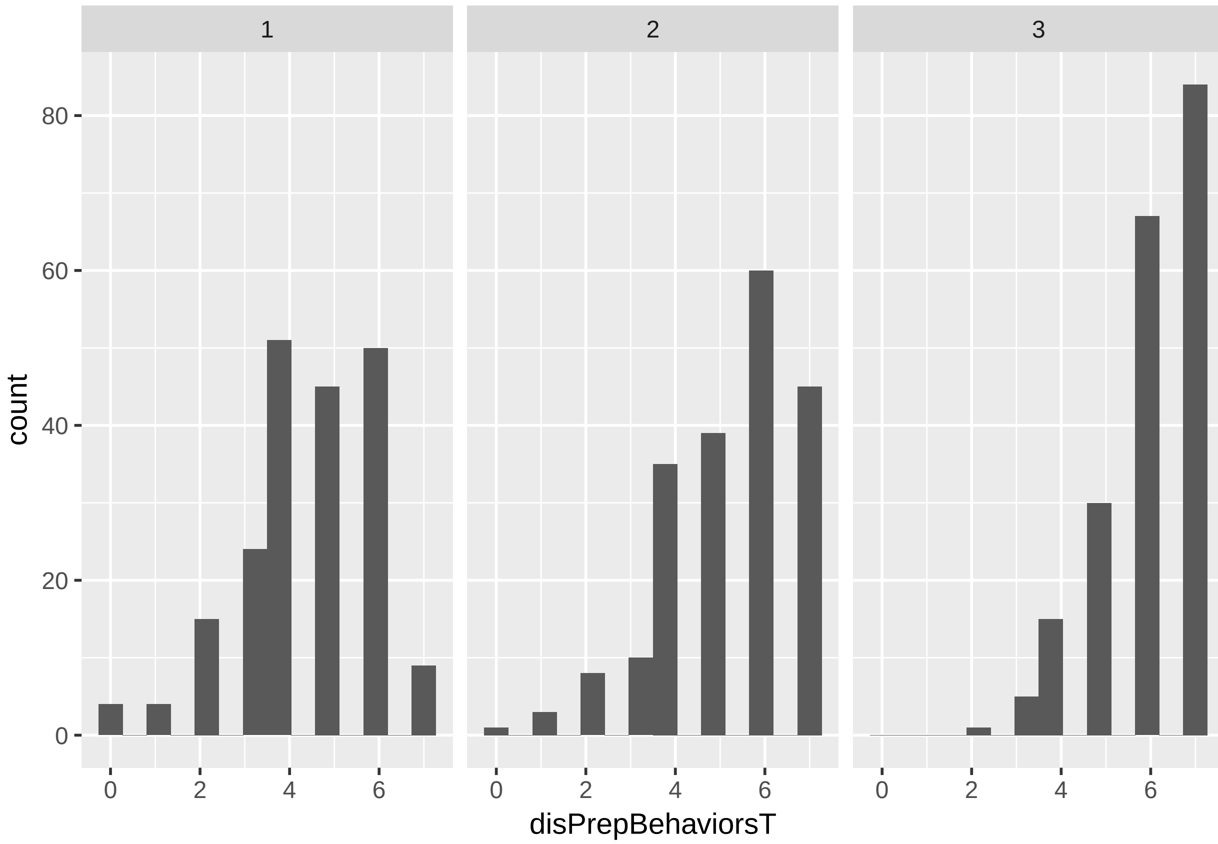
```r
t.test(copingSubuse_T ~ gender, data = data, subset = timePoint == "1", var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  copingSubuse_T by gender
## t = -3.8488, df = 234, p-value = 0.0001532
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.4197678 -0.1355214
## sample estimates:
## mean in group Female   mean in group Male
##             1.147887             1.425532
```

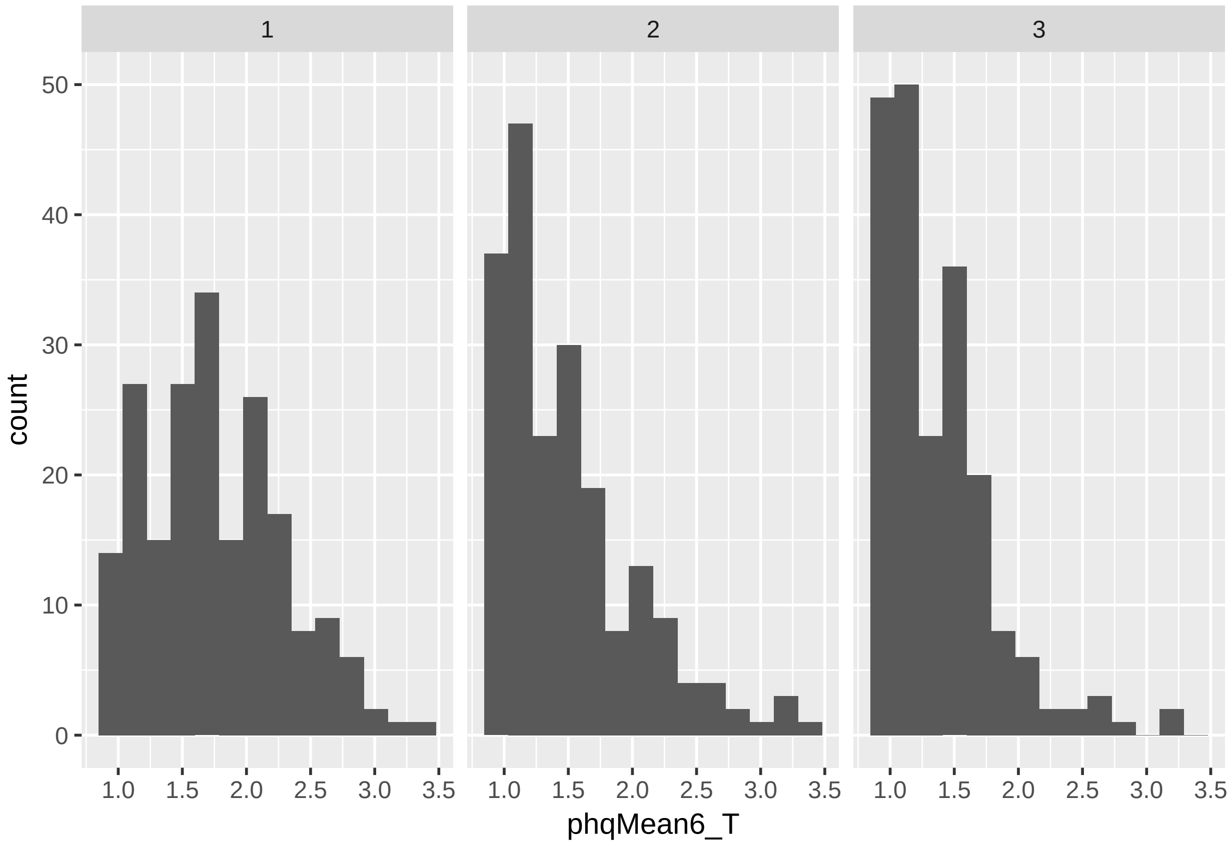
Next we take a look at histograms of key dependent measures faceted by time-point to see the shapes of their distributions. We plan to apply a linear model, so we need to understand to what degree that's appropriate and/or the most appropriate generalized linear model.

```r
dvs = c('disPrepBehaviorsT', 'phqMean6_T', 'ptsdMean11_T', 'HelpSeekingMentalT', 'HelpSeekingDisT', 'so

for(var in dvs) {
  print(ggplot(data = filtered, aes_string(x=var)) + geom_histogram(bins=14) + facet_grid(.~timePoint))
}
```

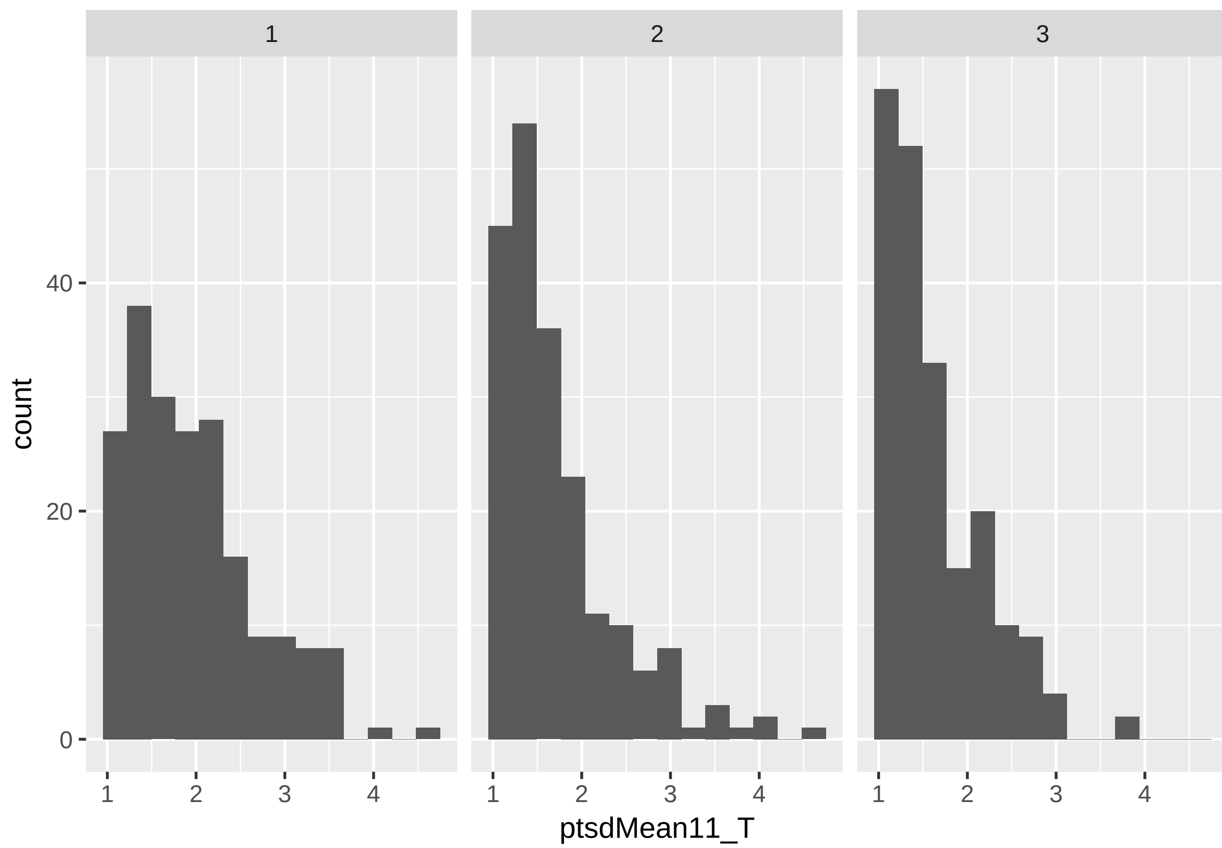
```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



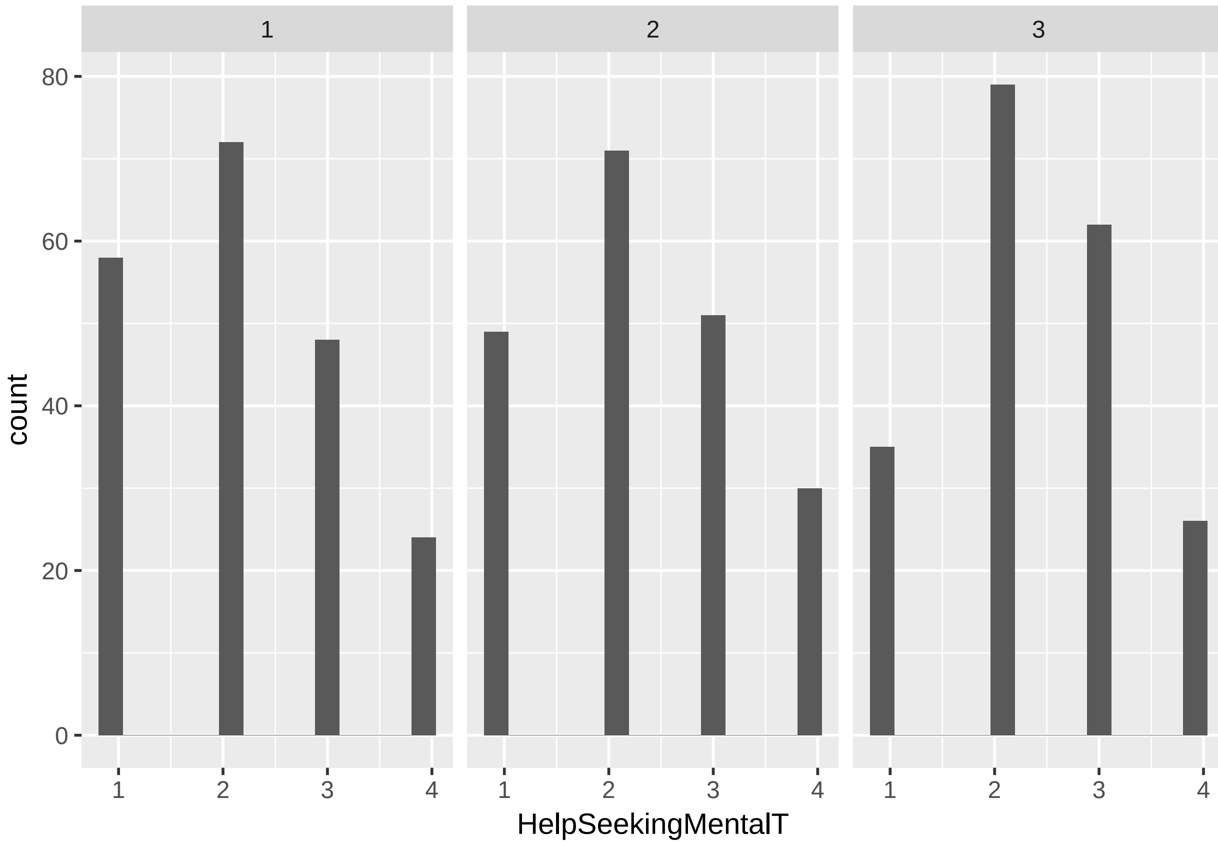

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



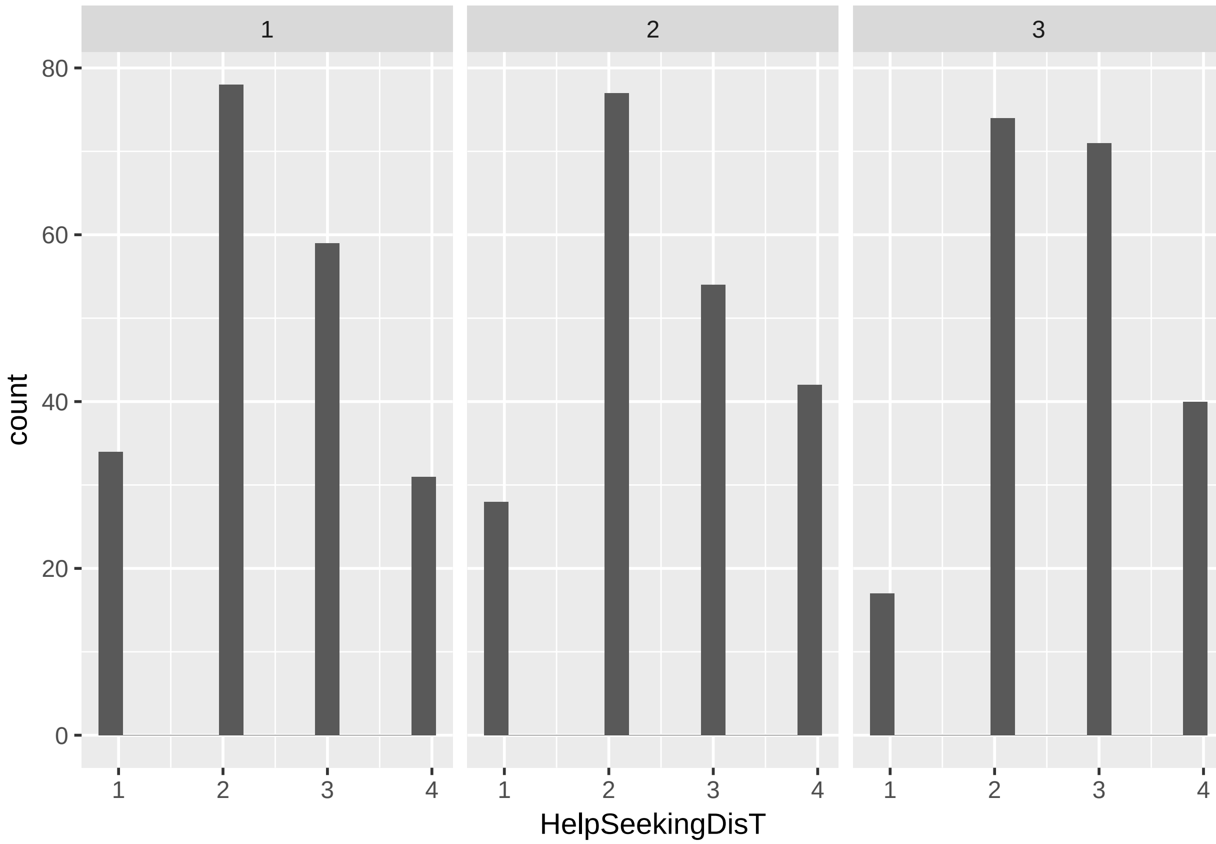

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



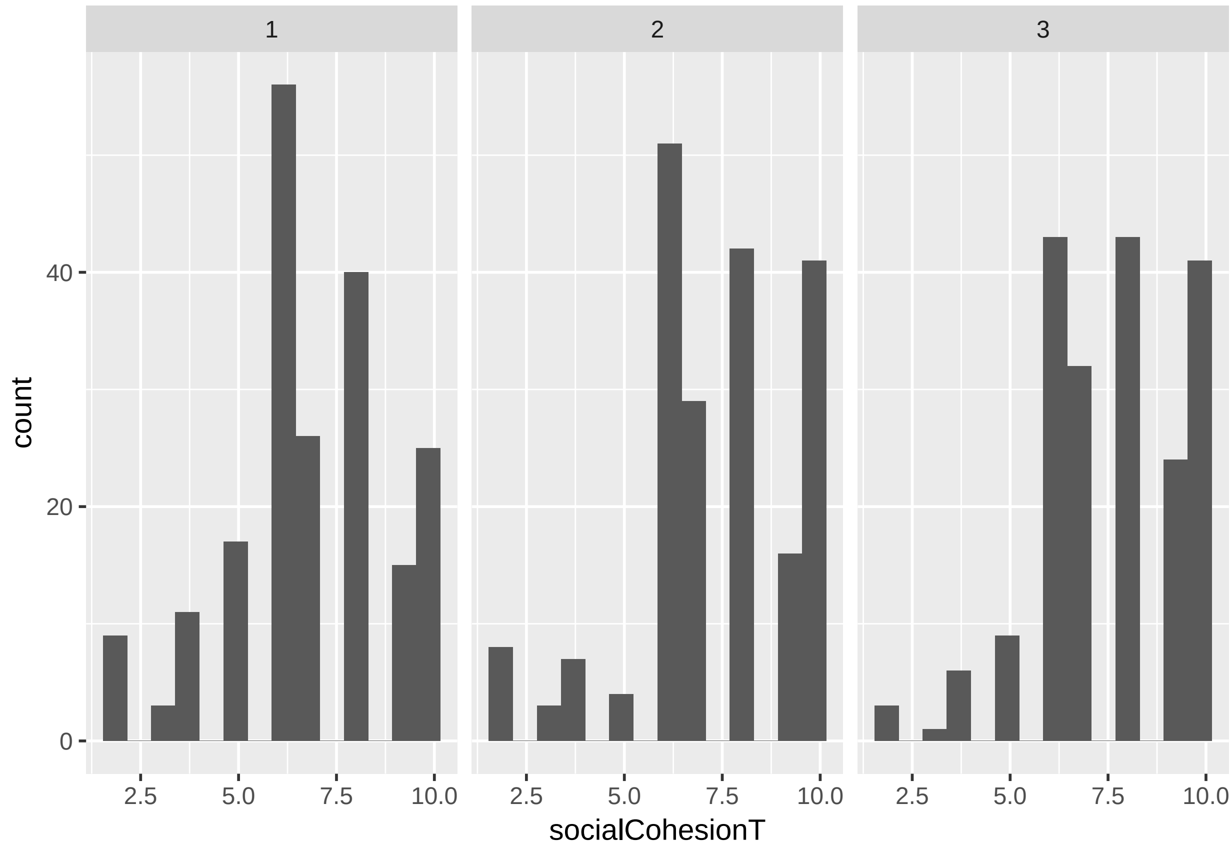

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```




```
## 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-intervent
                        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=interventPlot
        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_mar
        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 + interventionT + (1|city/ID), data=filte
disPrep <- glmer(cbind(disPrepBehaviorsT, disPrepSize-disPrepBehaviorsT) ~ timePoint + interventionT +
disPrepExcludedItems <- glmer(cbind(disPrepBehaviorsT, disPrepSize-disPrepBehaviorsT) ~ timePoint + inte
# here because we use a binomial family model, we cannot use RLRsim to test the random effects; however
anova(disPrep, disPrepExcludedItems)
```

```
## Data: filtered
## Models:
## disPrepExcludedItems: cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT) ~ timePoint +
## disPrepExcludedItems:     interventionT + (1 | ID)
## disPrep: cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT) ~ timePoint +
## disPrep:     interventionT + (1 | city/ID)
##                      Df    AIC    BIC  logLik deviance  Chisq Chi Df
## disPrepExcludedItems  5 1841.9 1863.9 -915.93   1831.9
## disPrep               6 1830.8 1857.2 -909.40   1818.8 13.069      1
##                      Pr(>Chisq)
## disPrepExcludedItems
## disPrep               0.0003003 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# we'll also run a linear model to derive Cohen's d estimates later
disPrepLinear <- lmer(disPrepBehaviorsT ~ timePoint + interventionT + (1|city/ID), data=filtered)
disPrepExcludedItemsLinear <- lmer(disPrepBehaviorsExcludedItems_T ~ timePoint + interventionT + (1|city

summary(disPrep)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT) ~ timePoint +
##     interventionT + (1 | city/ID)
##    Data: filtered
##
##      AIC      BIC   logLik deviance df.resid
##   1830.8   1857.2   -909.4   1818.8      599
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.7625 -0.4682  0.1200  0.7373  2.3570
##
## Random effects:
##  Groups  Name        Variance Std.Dev.
##  ID:city (Intercept) 0.39895  0.6316
##  city    (Intercept) 0.07705  0.2776
## Number of obs: 605, groups:  ID:city, 203; city, 2
##
## Fixed effects:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  0.6213     0.2096   2.965 0.003028 **
## timePoint2                   0.3633     0.1091   3.331 0.000865 ***
```

```
## timePoint3                  0.7200     0.1965   3.664 0.000248 ***
## interventionTIntervention   0.6553     0.1673   3.918 8.92e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.136
## timePoint3  -0.069  0.675
## intrvntnTIn -0.011 -0.593 -0.866
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: cbind(disPrepBehaviorsT, disPrepSize - disPrepBehaviorsT)
##                   Chisq Df Pr(>Chisq)
## (Intercept)     8.7903  1  0.0030283 **
## timePoint      14.7746  2  0.0006191 ***
## interventionT 15.3521  1  8.922e-05 ***
## ---
## 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

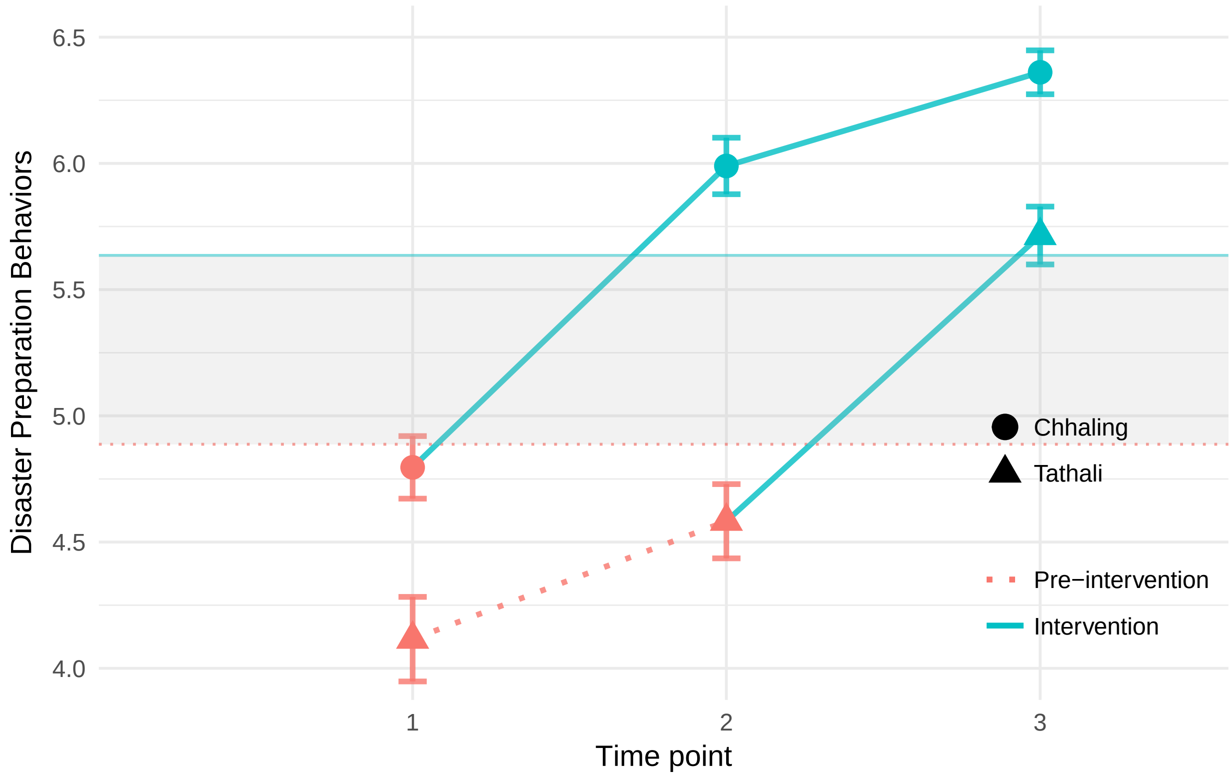
Have to pre-determine y-axis limits to equate them between panels. Pass marginal means of intervention effect to function.

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

```
##  interventionT   lsmean        SE   df lower.CL upper.CL
##  Control       4.887471 0.3437059 1.14 1.586793 8.188149
##  Intervention  5.635508 0.3435991 1.14 2.335856 8.935160
##
## Results are averaged over the levels of: timePoint
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```r
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).
```

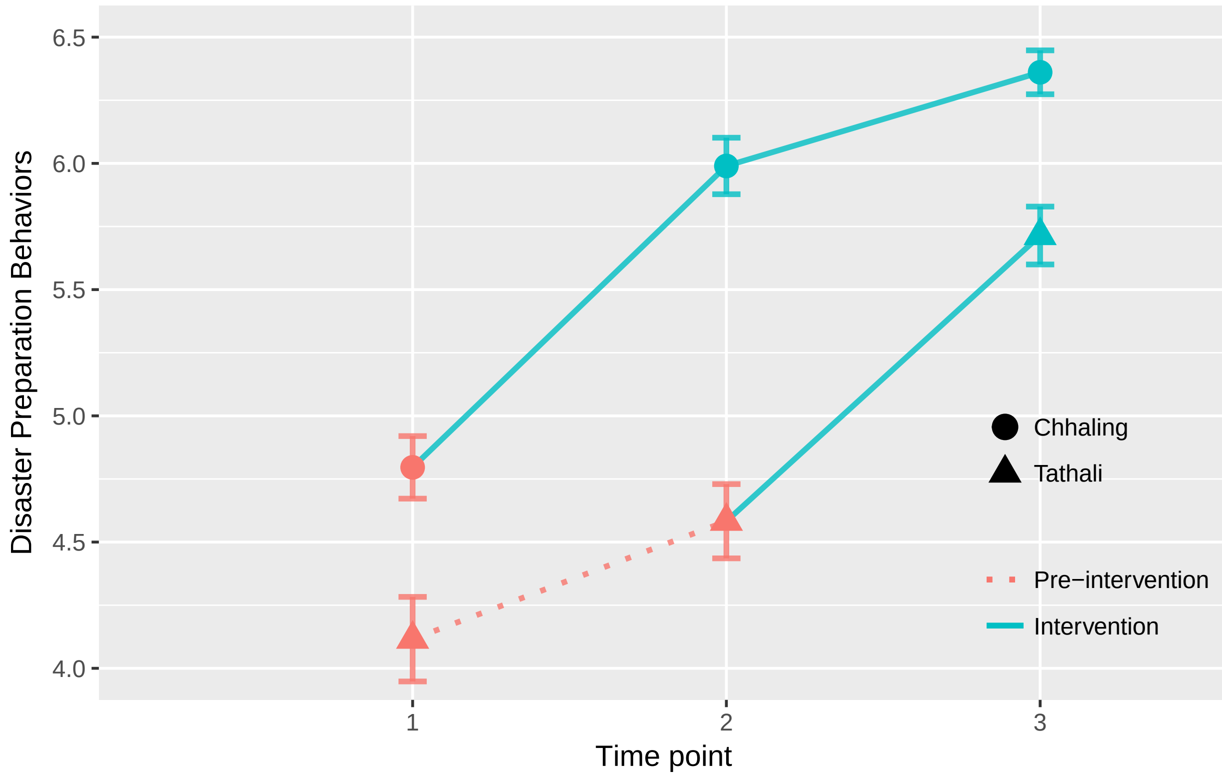


Seven−item yes/no scale (range 0 − 7), with greater values indicating greater engagement in disa
behaviors. Shaded region depicts size of difference between pre− and post−intervention marginal

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

```
# 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 + interventionT + (1 | ID)
##    Data: filtered
##
## REML criterion at convergence: 708.4
##
```

```
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.7552 -0.5537 -0.0639  0.4284  3.4496
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.1159   0.3404
##  Residual             0.1158   0.3403
## Number of obs: 605, groups:  ID, 203
##
## Fixed effects:
##                             Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                  1.77399    0.03384 402.00000  52.428  < 2e-16
## timePoint2                  -0.13926    0.04343 434.30000  -3.206  0.00144
## timePoint3                  -0.13496    0.06509 466.00000  -2.073  0.03868
## interventionTIntervention  -0.25755    0.05548 489.90000  -4.642 4.43e-06
##
## (Intercept)                ***
## timePoint2                 **
## timePoint3                 *
## interventionTIntervention ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.392
## timePoint3  -0.262  0.736
## intrvntnTIn  0.001 -0.624 -0.854
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: phqMean6_T
##                  Chisq Df Pr(>Chisq)
## (Intercept)   2748.662  1  < 2.2e-16 ***
## timePoint       10.460  2   0.005355 **
## interventionT   21.549  1  3.448e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

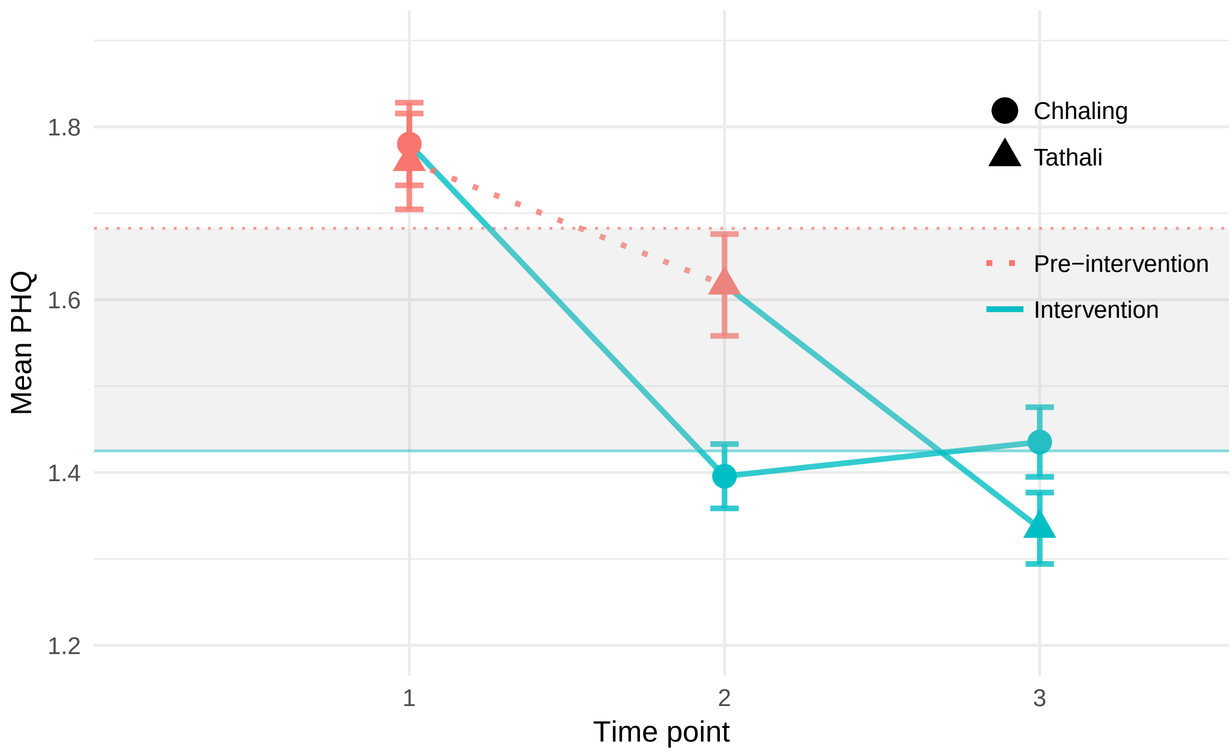
```r
mmeans <- lsmeans::lsmeans(phq, ~interventionT)  #marginal means
summary(mmeans)
```

```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       1.682586 0.03897949 491.20 1.605999 1.759173
##  Intervention  1.425039 0.03930445 497.13 1.347813 1.502264
##
## Results are averaged over the levels of: timePoint
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```r
limits <- c(1.2,1.9)
theme <- theme_minimal()
#rnge <- range(filtered$phqMean6_T, na.rm = TRUE)'
```

```r
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.

```r
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
```

```r
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
```

```r
mA <- lmer(ptsdMean11_T ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- lmer(ptsdMean11_T ~ timePoint + interventionT + (1|ID), data=filtered)
m <- lmer(ptsdMean11_T ~ timePoint + interventionT + (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 = 0.026971, p-value = 0.2591
```

```r
#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 + interventionT + (1 | ID)
##    Data: filtered
##
## REML criterion at convergence: 964.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8748 -0.5433 -0.0638  0.4801  3.9990
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.2704   0.5200
##  Residual             0.1519   0.3897
## Number of obs: 605, groups:  ID, 203
##
## Fixed effects:
##                             Estimate Std. Error        df t value Pr(>|t|)
```

```
## (Intercept)                  1.96482    0.04567 331.00000  43.023  < 2e-16
## timePoint2                  -0.12514    0.05017 422.00000  -2.494    0.013
## timePoint3                  -0.07870    0.07573 442.70000  -1.039    0.299
## interventionTIntervention  -0.27433    0.06490 458.10000  -4.227 2.86e-05
##
## (Intercept)                ***
## timePoint2                 *
## timePoint3
## interventionTIntervention ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.330
## timePoint3  -0.219  0.741
## intrvntnTIn  0.001 -0.632 -0.859
```

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

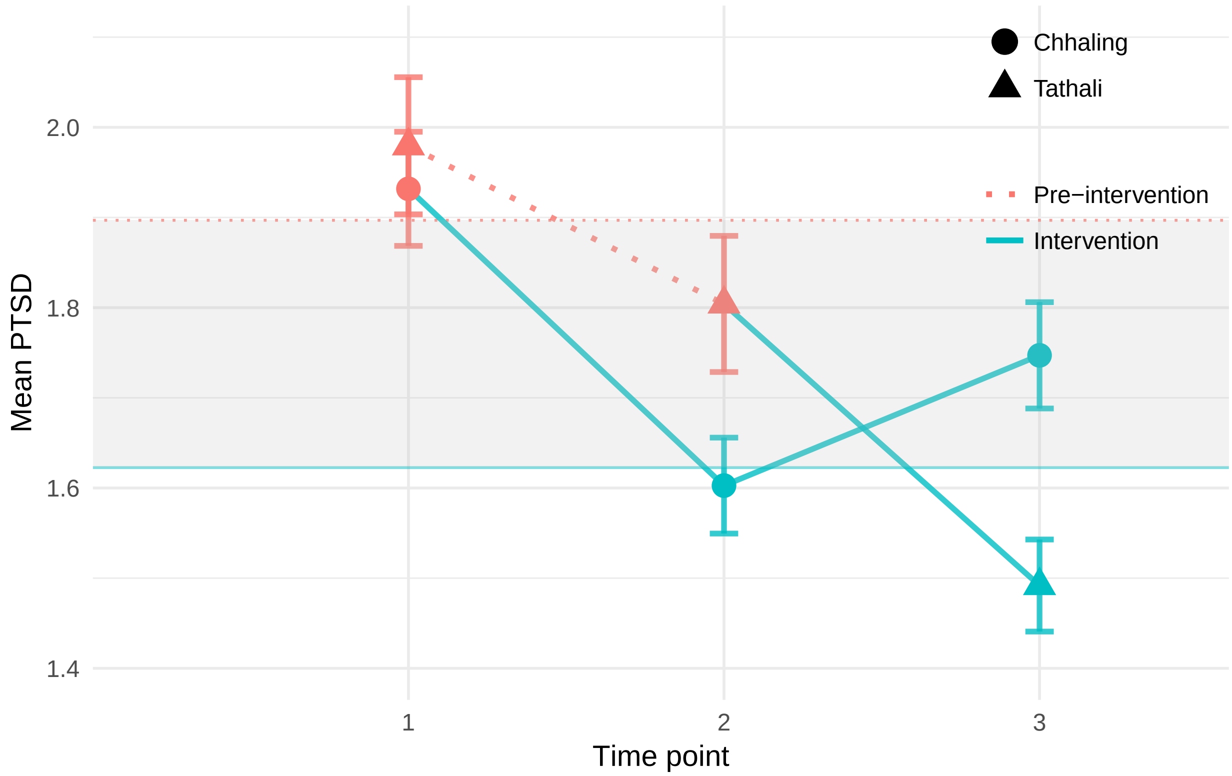
```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: ptsdMean11_T
##                   Chisq Df Pr(>Chisq)
## (Intercept)   1850.9755  1  < 2.2e-16 ***
## timePoint        7.6709  2    0.02159 *
## interventionT   17.8672  1  2.369e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       1.896876 0.05118236 428.23 1.796276 1.997476
##  Intervention  1.622544 0.05152112 434.31 1.521278 1.723810
##
## Results are averaged over the levels of: timePoint
## 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 expi
plot_line_bar("ptsdMean11_T", limits, mmeans, theme, "Mean PTSD", position=c(.8825, .805), by=.2, captio
```

```
## 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
```

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

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: HelpSeekingMentalT ~ timePoint + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  605  -774.00 1562.00 380(1144) 1.15e-03 4.2e+01
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 1.544    1.243
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                 -0.08835    0.24522  -0.360   0.7186
## timePoint3                 -0.26172    0.35410  -0.739   0.4598
## interventionTIntervention  0.75934    0.30090   2.524   0.0116 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2  -1.2852     0.1815  -7.082
## 2|3   0.8077     0.1750   4.615
## 3|4   2.6772     0.2192  12.215
## (4 observations deleted due to missingness)
```

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

```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingMentalT
##                LR Chisq Df Pr(>Chisq)
## timePoint        0.6231  2    0.73233
## interventionT    6.4194  1    0.01129 *
## ---
```

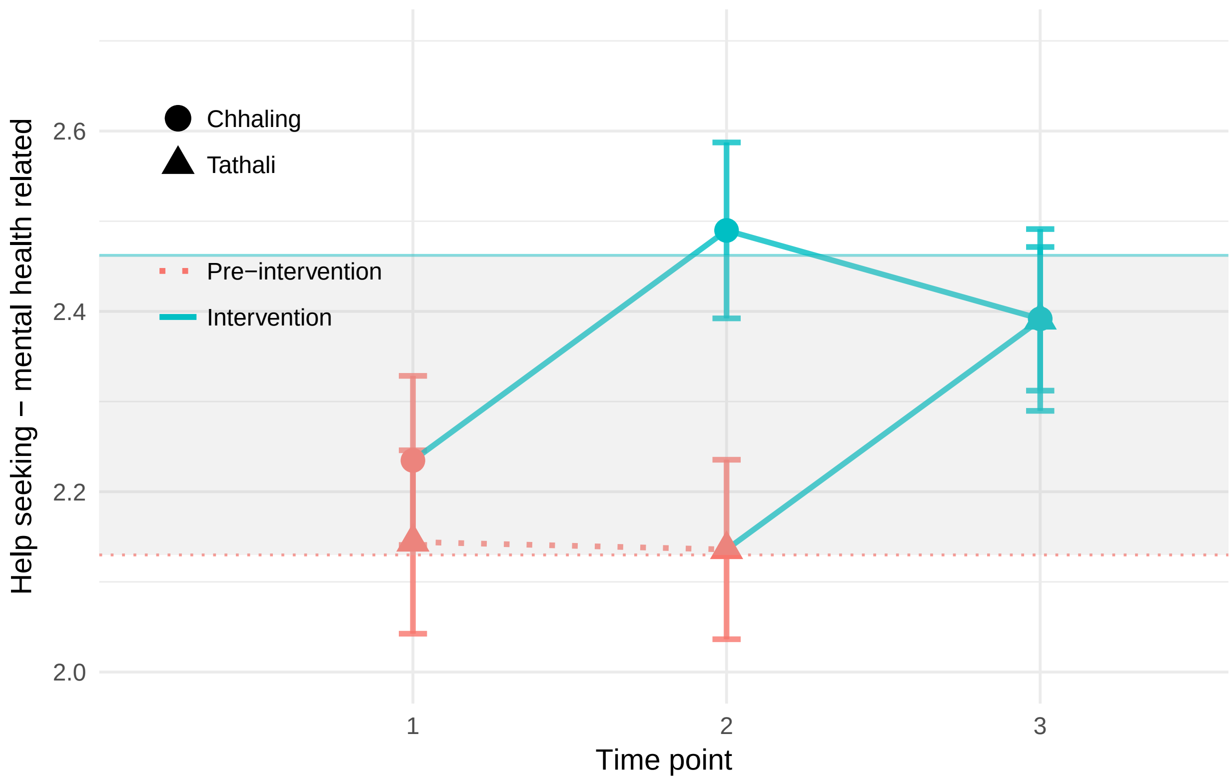
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       2.129883 0.07990125 539.49 1.972927 2.286838
##  Intervention  2.462123 0.08072715 543.87 2.303545 2.620701
##
## Results are averaged over the levels of: timePoint
## 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_seeking_mentalCity <- clmm(HelpSeekingMentalT ~ timePoint * city + (1|ID), data=filtered)
Anova(help_seeking_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_seeking_mentalCityMM <- lsmeans::lsmeans(help_seeking_mentalCity, ~ timePoint * city)
summary(rbind(pairs(help_seeking_mentalCityMM, by="city")[c(1,3,4,6)], pairs(help_seeking_mentalCityMM,
```

```
##  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
```

For disaster-related help-seeking, we additionally want to explore a model with interactions with gender because outside analyses gave us reason to believe there would be gender-specific effects.

```
#mA <- clmm(HelpSeekingDisT ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(HelpSeekingDisT ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(HelpSeekingDisT ~ timePoint + interventionT + (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_seeking_dis <- m0
help_seeking_dis_linear <- lmer(as.numeric(HelpSeekingDisT) ~ timePoint + interventionT + (1|ID), data =
summary(help_seeking_dis)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: HelpSeekingDisT ~ timePoint + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  605  -757.74 1529.47 431(1677) 2.48e-04 4.3e+01
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 1.864    1.365
## Number of groups:  ID 203
```

```
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## timePoint2                -0.05769    0.25078  -0.230   0.8180
## timePoint3                -0.09498    0.36071  -0.263   0.7923
## interventionTIntervention  0.68795    0.30943   2.223   0.0262 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2  -2.2277     0.2121 -10.501
## 2|3   0.3505     0.1771   1.979
## 3|4   2.2887     0.2109  10.853
## (4 observations deleted due to missingness)
```

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

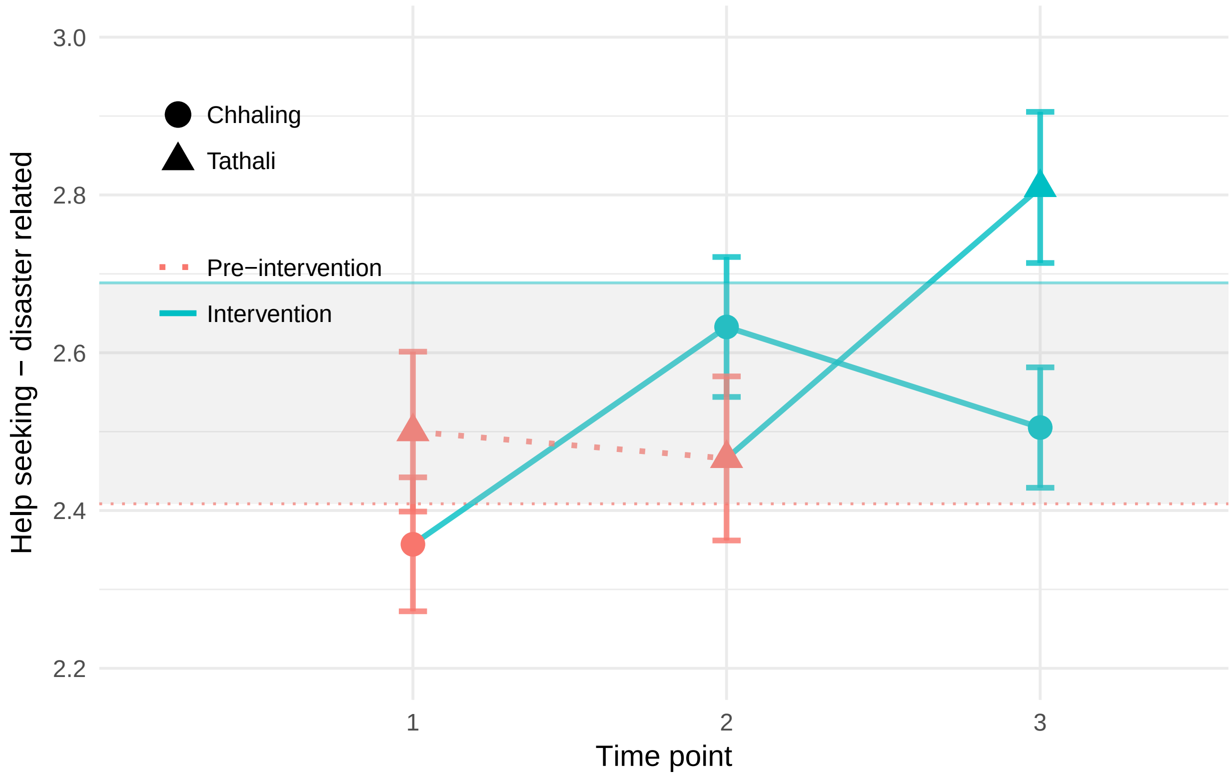
```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingDisT
##                LR Chisq Df Pr(>Chisq)
## timePoint        0.0719  2    0.96470
## interventionT    5.0332  1    0.02487 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
##  interventionT   lsmean         SE     df lower.CL upper.CL
##  Control       2.408522 0.07739095 534.02 2.256494  2.56055
##  Intervention  2.688521 0.07816540 538.70 2.534971  2.84207
##
## Results are averaged over the levels of: timePoint
## 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_seeking_disCity <- clmm(HelpSeekingDisT ~ timePoint * city + (1|ID), data=filtered)
Anova(help_seeking_disCity, 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_seeking_disCityMM <- lsmeans::lsmeans(help_seeking_disCity, ~ timePoint * city)
summary(rbind(pairs(help_seeking_disCityMM, by="city")[c(1,3,4,6)], pairs(help_seeking_disCityMM, by="t
```

```
##  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
```

```r
help_seeking_dis_gender <- clmm(HelpSeekingDisT ~ timePoint * gender + interventionT * gender + (1|ID),
summary(help_seeking_dis_gender)
```

```
## 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)
```

```r
Anova(help_seeking_dis_gender, 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
```

For social cohesion we also want to explore a model with interactions with gender.

```
mA <- lmer(socialCohesionT ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- lmer(socialCohesionT ~ timePoint + interventionT + (1|ID), data=filtered)
m <- lmer(socialCohesionT ~ timePoint + interventionT + (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 = 4.3657, p-value = 0.0053
```

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

soc_coh_gender <- lmer(socialCohesionT ~ timePoint * gender + interventionT * gender + (1|city/ID), data

summary(soc_coh)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
## Formula: socialCohesionT ~ timePoint + interventionT + (1 | city/ID)
##    Data: filtered
##
## REML criterion at convergence: 2488.4
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.11957 -0.52882  0.01869  0.62887  2.51558
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID:city  (Intercept) 1.036    1.0179
##  city     (Intercept) 0.154    0.3925
##  Residual             2.757    1.6603
## Number of obs: 605, groups:  ID:city, 203; city, 2
##
## Fixed effects:
##                             Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                  6.81587    0.30950   1.20000  22.022  0.01835
## timePoint2                   0.10711    0.21562 390.90000   0.497  0.61963
## timePoint3                  -0.05167    0.32846 357.70000  -0.157  0.87508
```

```
## interventionTIntervention   0.80193    0.28329 326.40000   2.831  0.00493
##
## (Intercept)               *
## timePoint2
## timePoint3
## interventionTIntervention **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.202
## timePoint3  -0.131  0.747
## intrvntnTIn -0.004 -0.641 -0.864
```

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

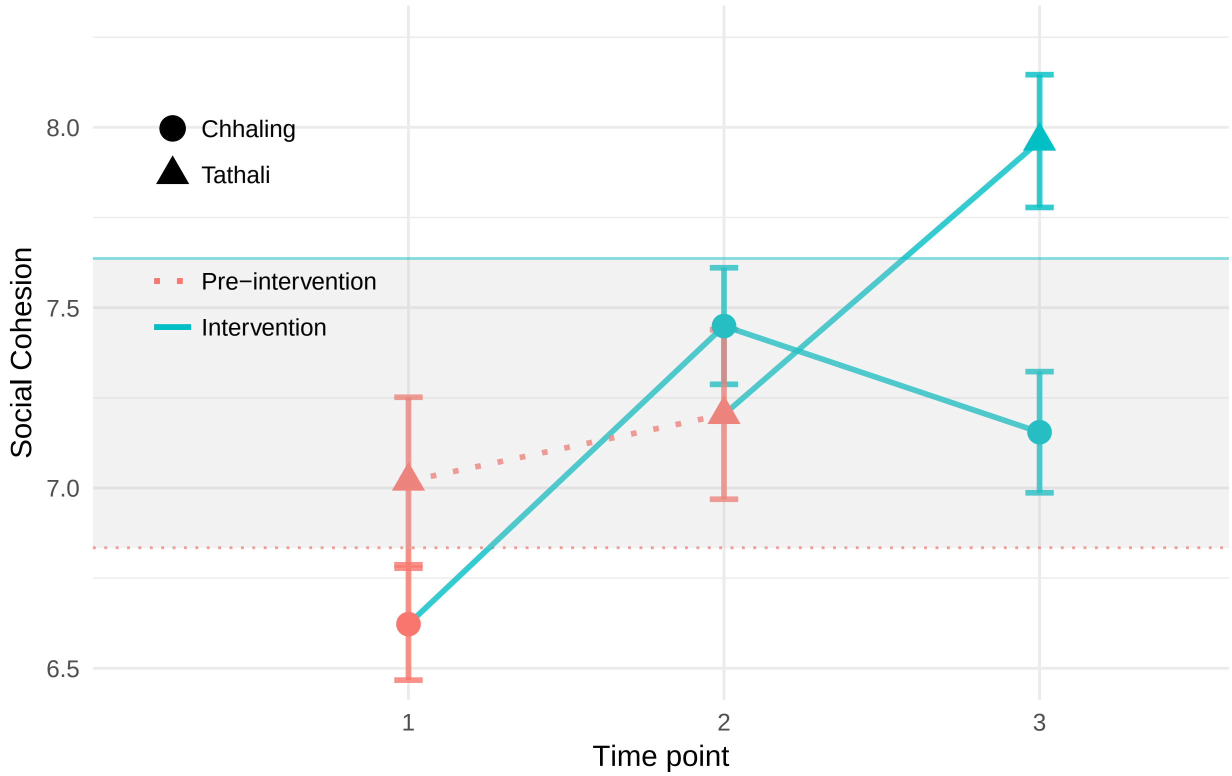
```
## Analysis of Deviance Table (Type II tests)
##
## Response: HelpSeekingDisT
##               LR Chisq Df Pr(>Chisq)
## timePoint       0.0719  2    0.96470
## interventionT   5.0332  1    0.02487 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
##  interventionT   lsmean        SE   df lower.CL upper.CL
##  Control       6.834350 0.3268222 1.42 4.711156 8.957544
##  Intervention  7.636282 0.3266525 1.42 5.514191 9.758374
##
## Results are averaged over the levels of: timePoint
## 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
```

```r
soc_coh_gender <- lmer(socialCohesionT ~ timePoint * gender + interventionT * gender + (1|city/ID), data
summary(soc_coh_gender)
```

```
## 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(soc_coh_gender, type = "III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: socialCohesionT
##                         Chisq Df Pr(>Chisq)
## (Intercept)          404.9391  1  < 2.2e-16 ***
## timePoint              3.1677  2  0.2051873
## gender                 1.9939  1  0.1579344
## interventionT         12.4892  1  0.0004093 ***
## timePoint:gender       6.3791  2  0.0411896 *
## gender:interventionT   3.3635  1  0.0666545 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

And we'll add a post-hoc power analyses for some of our main models using the `SWSamp` package along with `sjstats` to calculate ICC. The actual calls to `make.power()` are commented because of a bug that interferes with knitting to PDF.

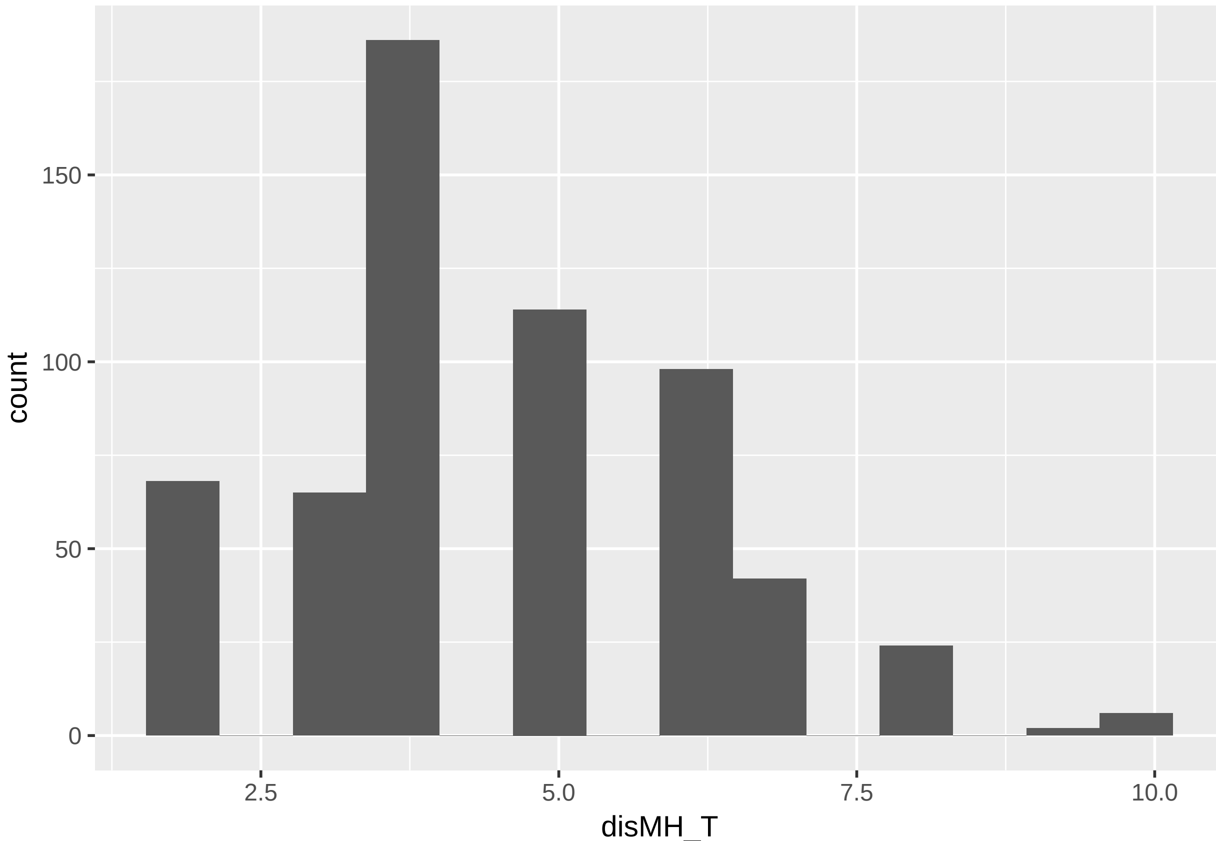
```
# disaster-preparedness behaviors, using estimations from the linear model
icc_df <- icc(disPrepLinear)
mu <- mean(filtered[filtered$timePoint == "1",]$disPrepBehaviorsT, na.rm=TRUE)
sw.trial <- function() {
  make.swt(I=2, J=2, H=1, K=120, design='cohort', mu=4.445545, b.trt=0.7480, b.time=0.6494, sigma.e=1.05
}
#sim.power(data = sw.trial)

# depression
phq_nested <- lmer(phqMean6_T ~ timePoint + interventionT + (1|city/ID), data = filtered)
icc_df <- icc(phq_nested)
mu <- mean(filtered[filtered$timePoint == "1",]$phqMean6_T, na.rm=TRUE)
sw.trial <- function() {
  make.swt(I=2, J=2, H=1, K=120, design='cohort', mu=1.769802, b.trt=-0.25755, b.time=-0.13711, sigma.e
}
#sim.power(data = sw.trial)

# ptsd
ptsd_nested <- lmer(ptsdMean11_T ~ timePoint + interventionT + (1|city/ID), data = filtered)
icc_df <- icc(ptsd_nested)
mu <- mean(filtered[filtered$timePoint == "1",]$ptsdMean11_T, na.rm=TRUE)
sw.trial <- function() {
  make.swt(I=2, J=2, H=1, K=120, design='cohort', mu=1.956374, b.trt=-0.27841, b.time=-0.098875, sigma.
}
#sim.power(data = sw.trial)

# social cohesion
icc_df <- icc(soc_coh)
mu <- mean(filtered[filtered$timePoint == "1",]$socialCohesionT, na.rm=TRUE)
```

```r
sw.trial <- function() {
  make.swt(I=2, J=2, H=1, K=120, design='cohort', mu=6.826733, b.trt=0.80193, b.time=0.02772, sigma.e=1
}
#sim.power(data = sw.trial)

# help seeking - mental health
help_seeking_mental_nested <- lmer(as.numeric(HelpSeekingMentalT) ~ timePoint + interventionT + (1|city/
icc_df <- icc(help_seeking_mental_nested)
mu <- mean(as.numeric(filtered[filtered$timePoint == "1",]$HelpSeekingMentalT), na.rm=TRUE)
sw.trial <- function() {
  make.swt(I=2, J=2, H=1, K=120, design='cohort', mu=2.188119, b.trt=0.33224, b.time=-0.08305, sigma.e=(
}
#sim.power(data = sw.trial)

# help seeking - disaster related
help_seeking_dis_nested <- lmer(as.numeric(HelpSeekingDisT) ~ timePoint + interventionT + (1|city/ID), d
icc_df <- icc(help_seeking_dis_nested)
mu <- mean(as.numeric(filtered[filtered$timePoint == "1",]$HelpSeekingDisT), na.rm=TRUE)
sw.trial <- function() {
  make.swt(I=2, J=2, H=1, K=120, design='cohort', mu=2.430693, b.trt=0.36674, b.time=-0.099665, sigma.e=
}
#sim.power(data = sw.trial)
```

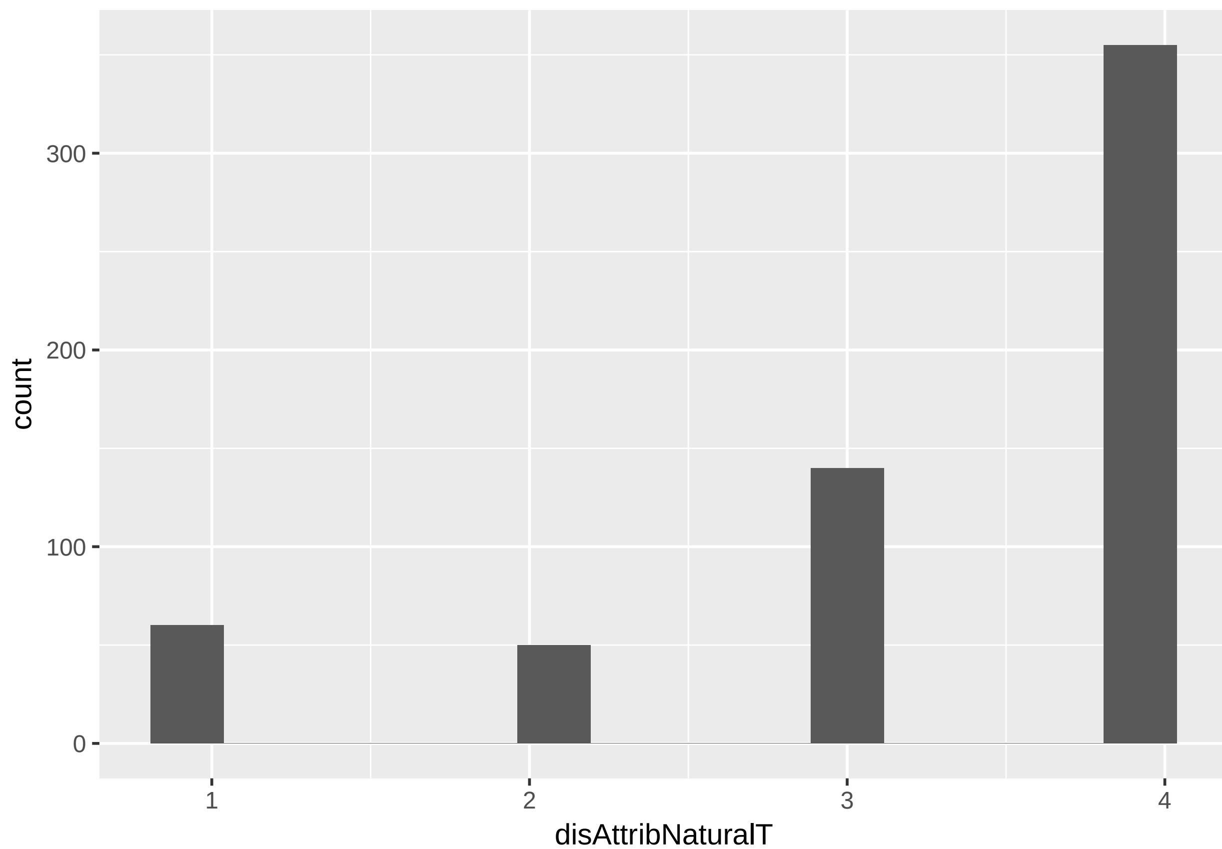
We'll do our other models without plotting the results. First let's look at their distributions.

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

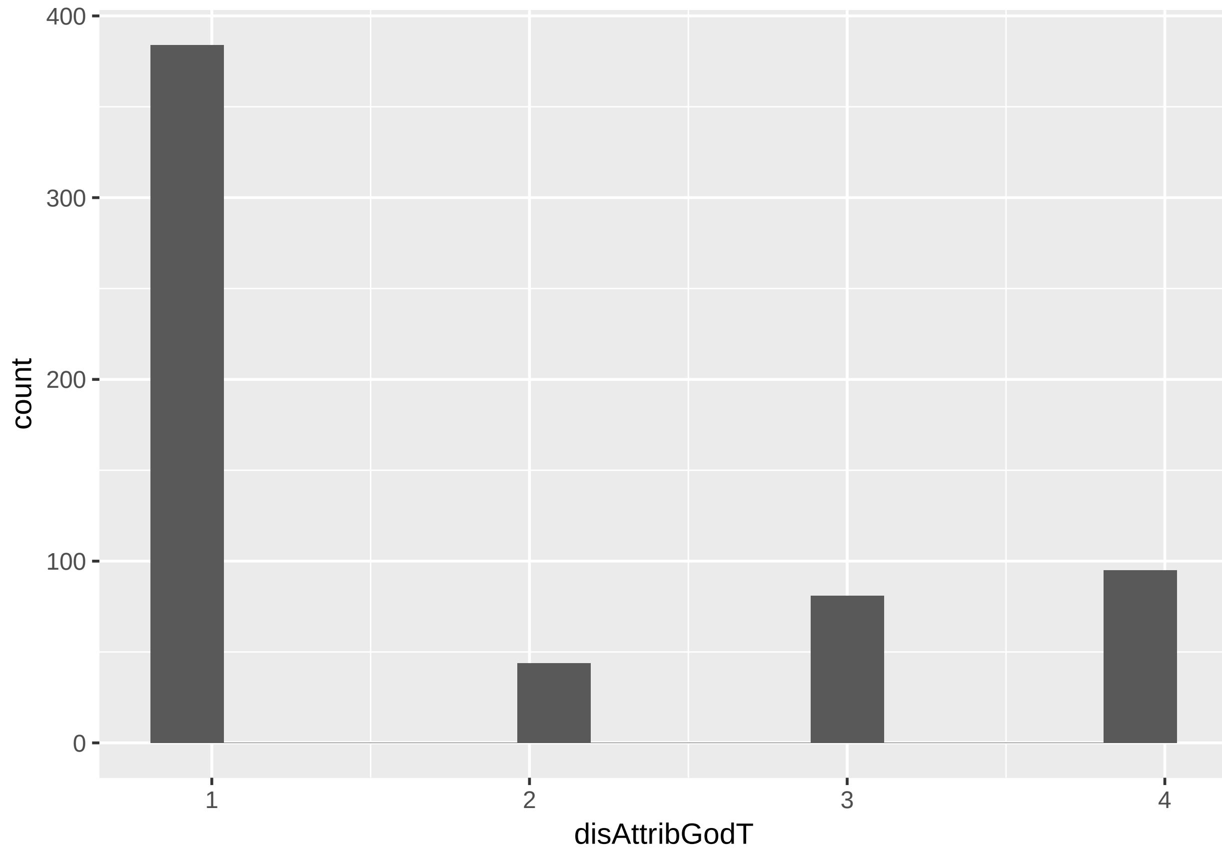
```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



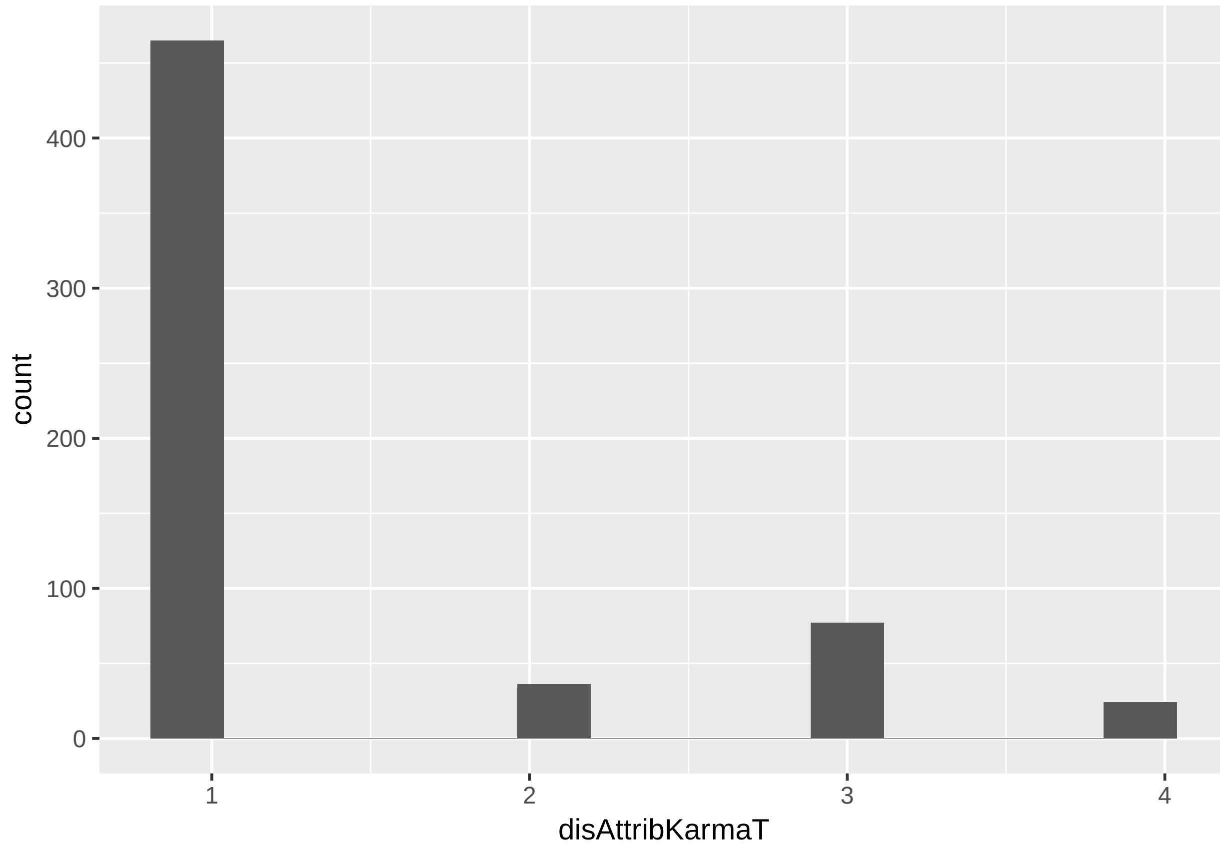

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



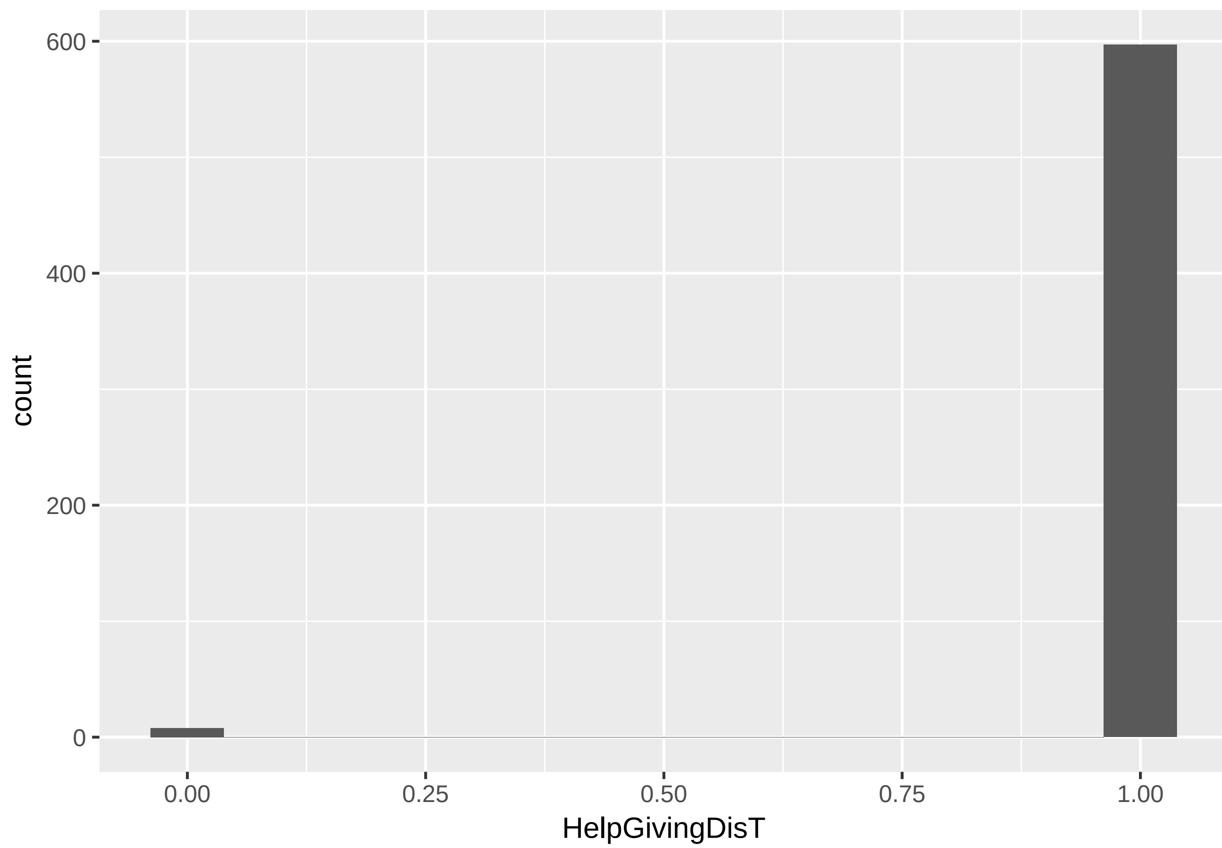

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```



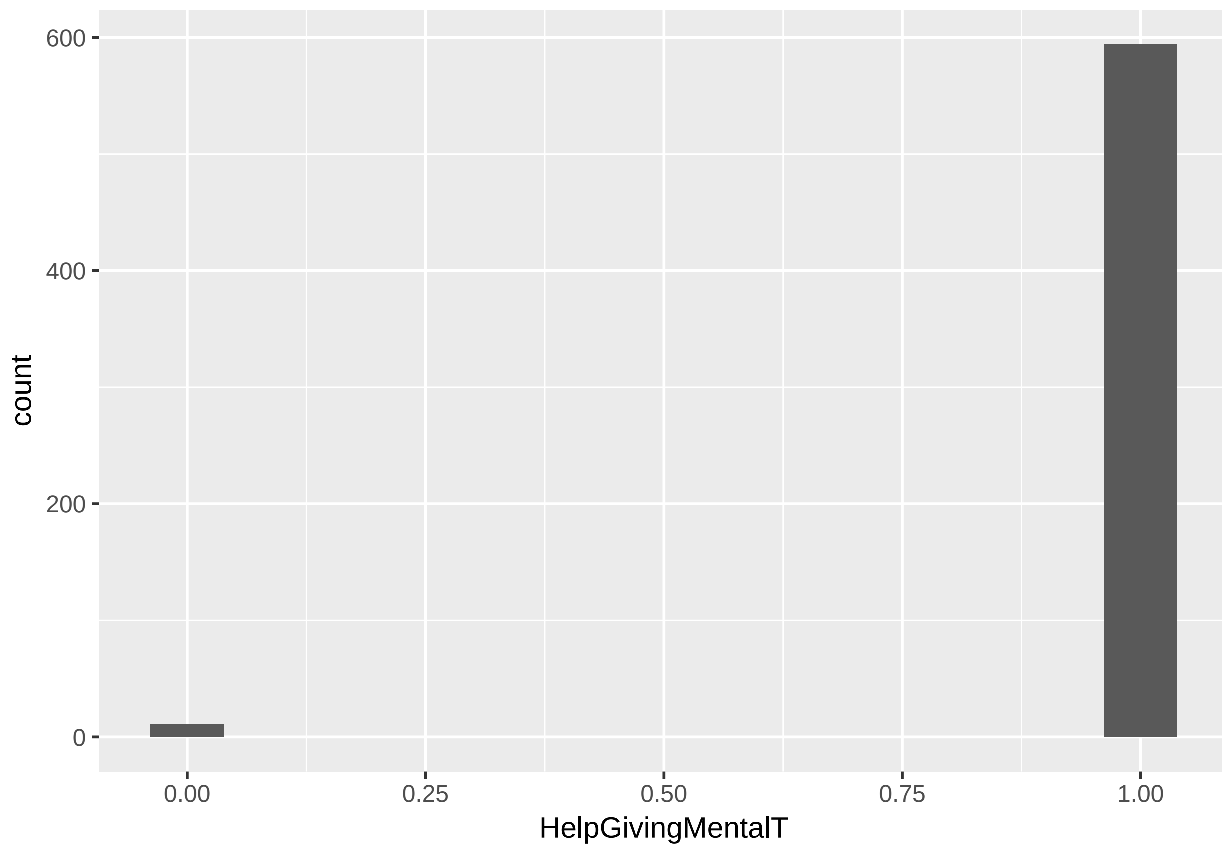

```
## Warning: Removed 7 rows containing non-finite values (stat_bin).
```



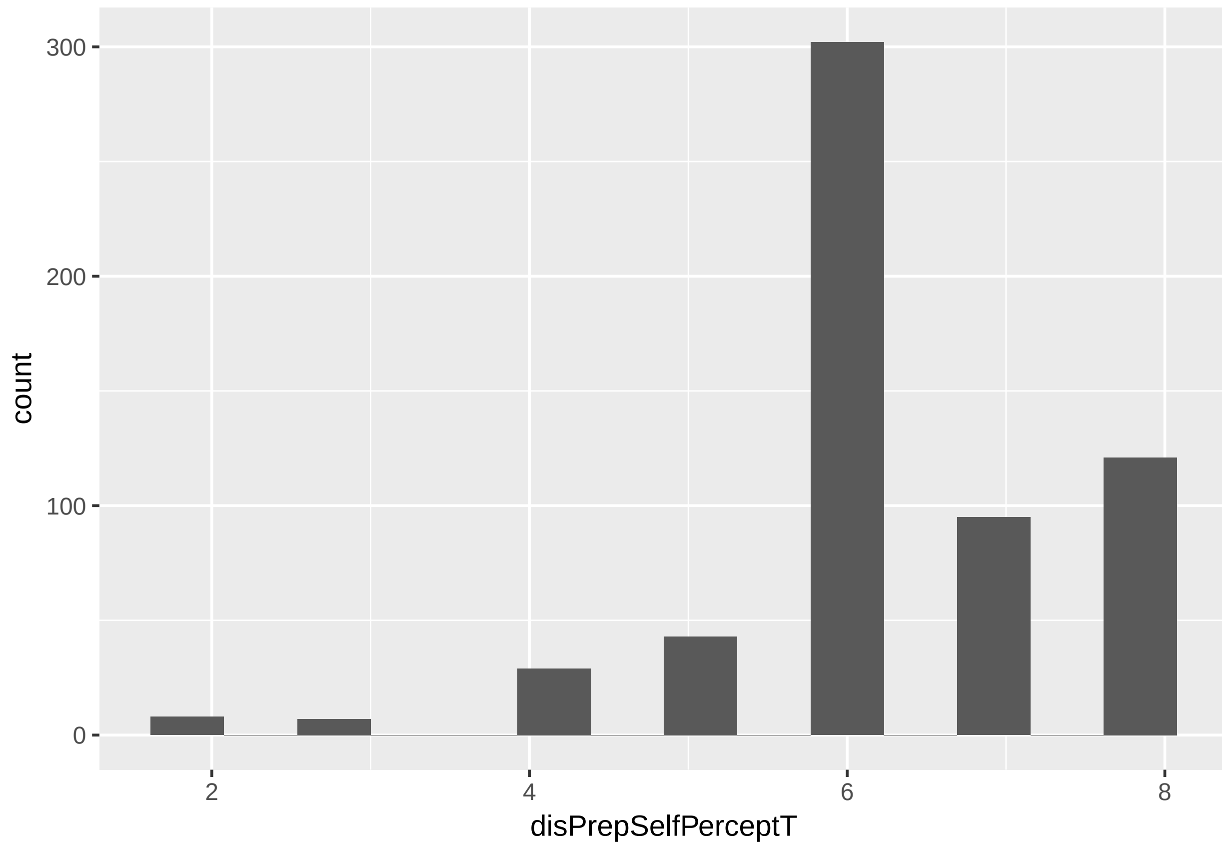

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



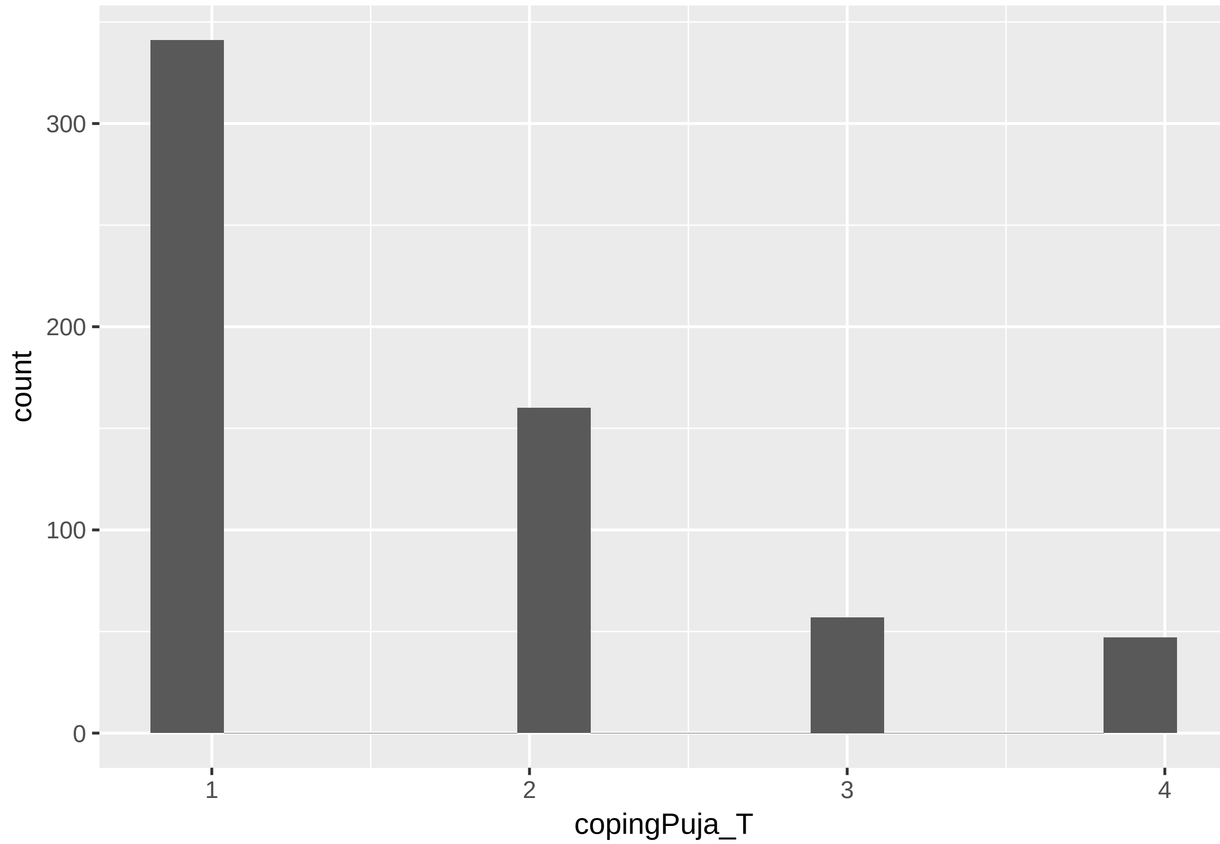

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



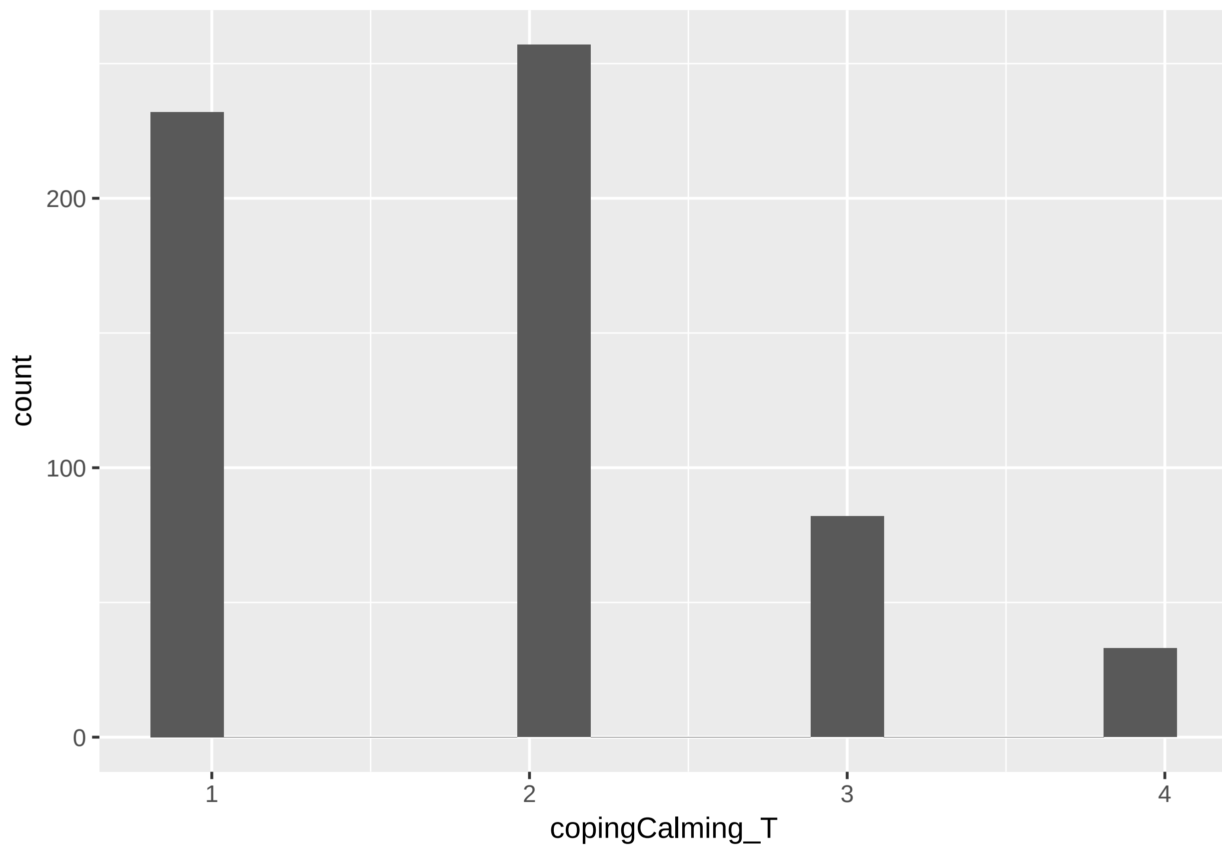

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



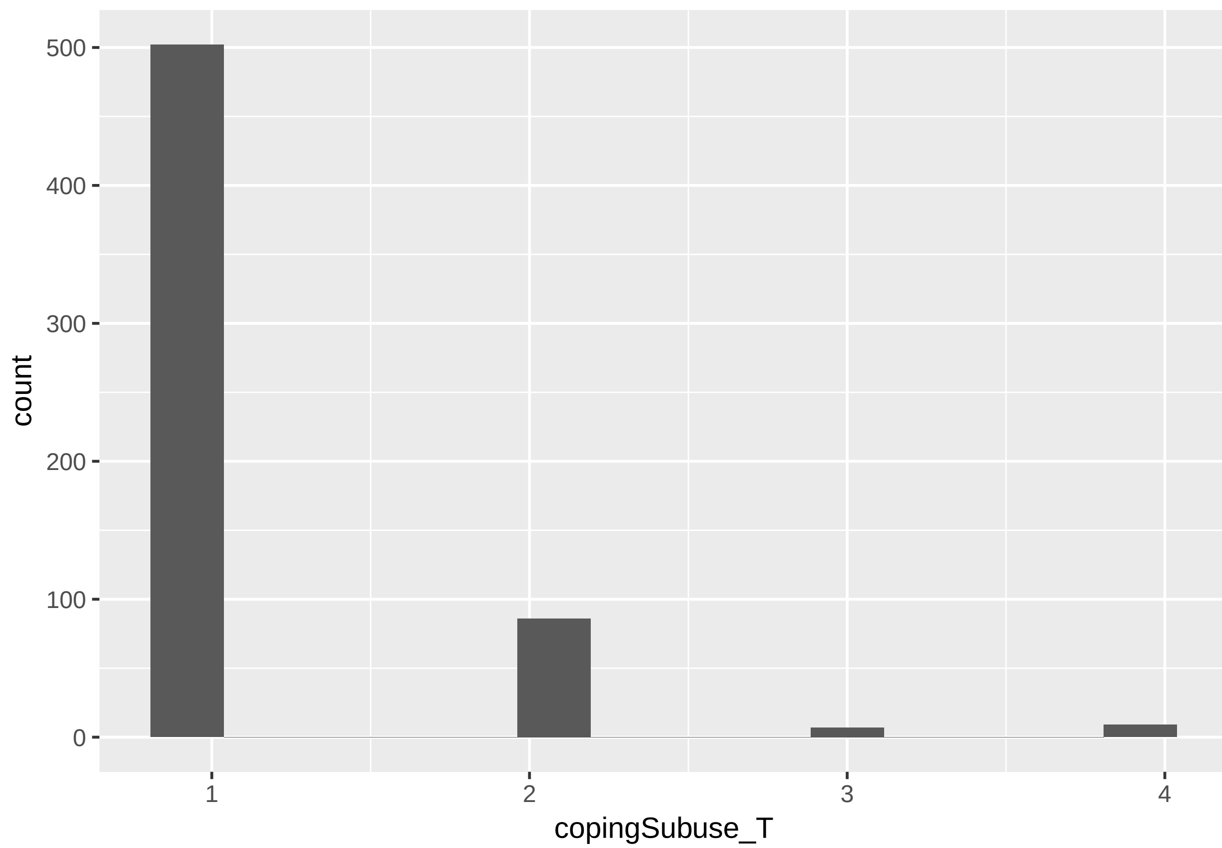

```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



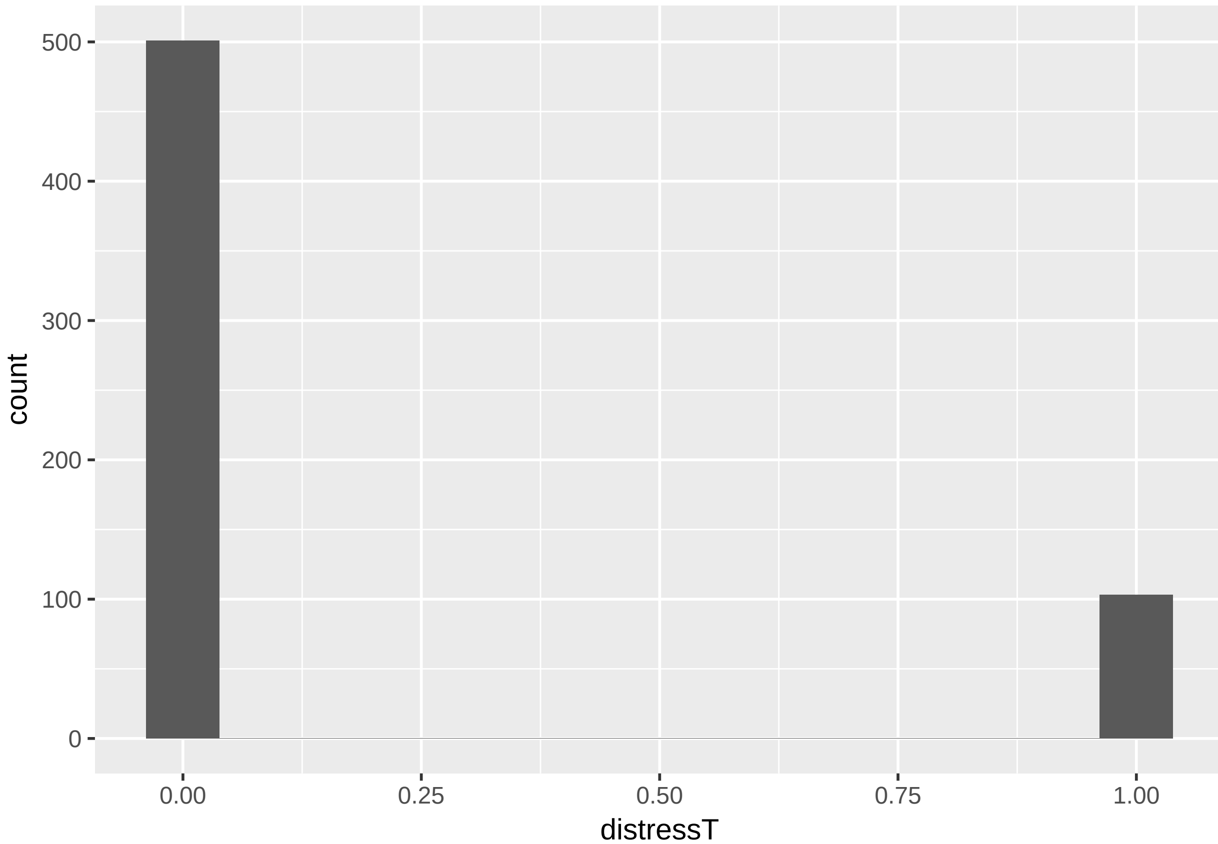

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```



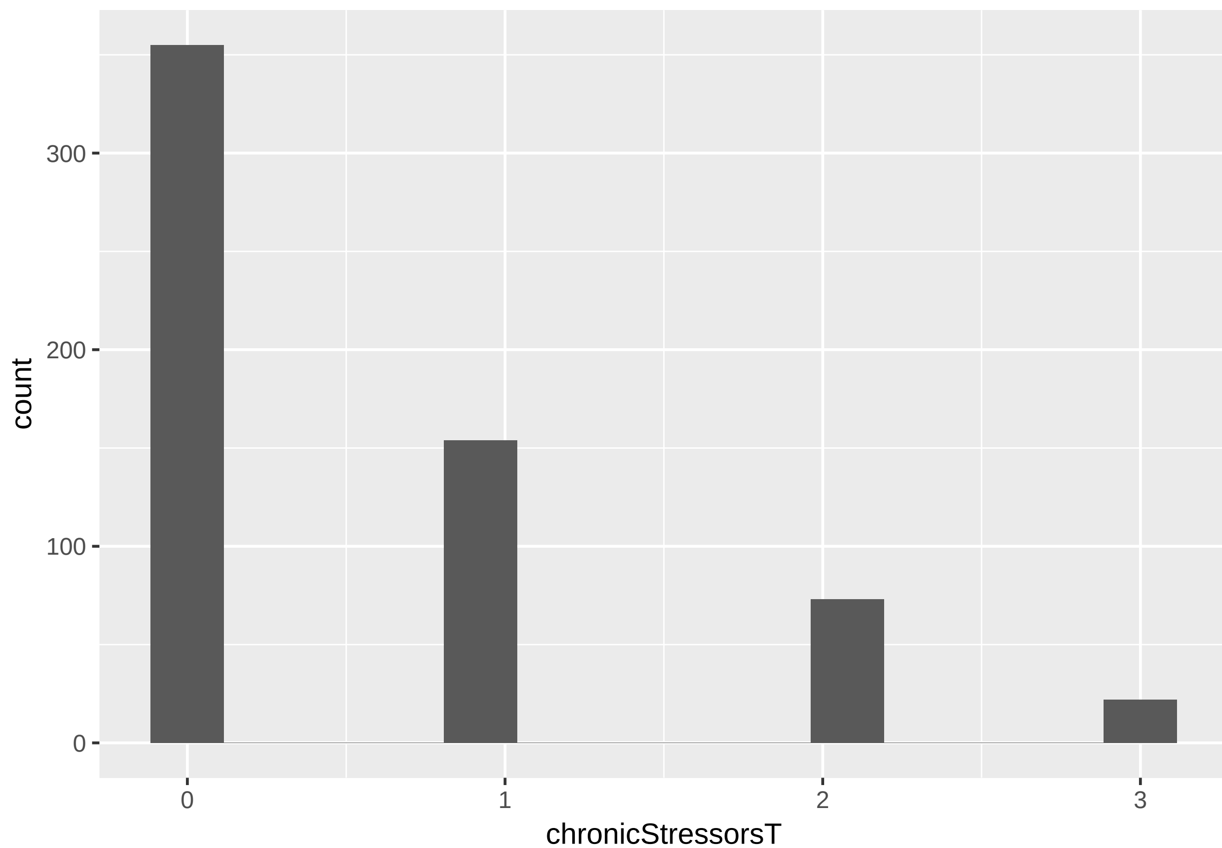

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```



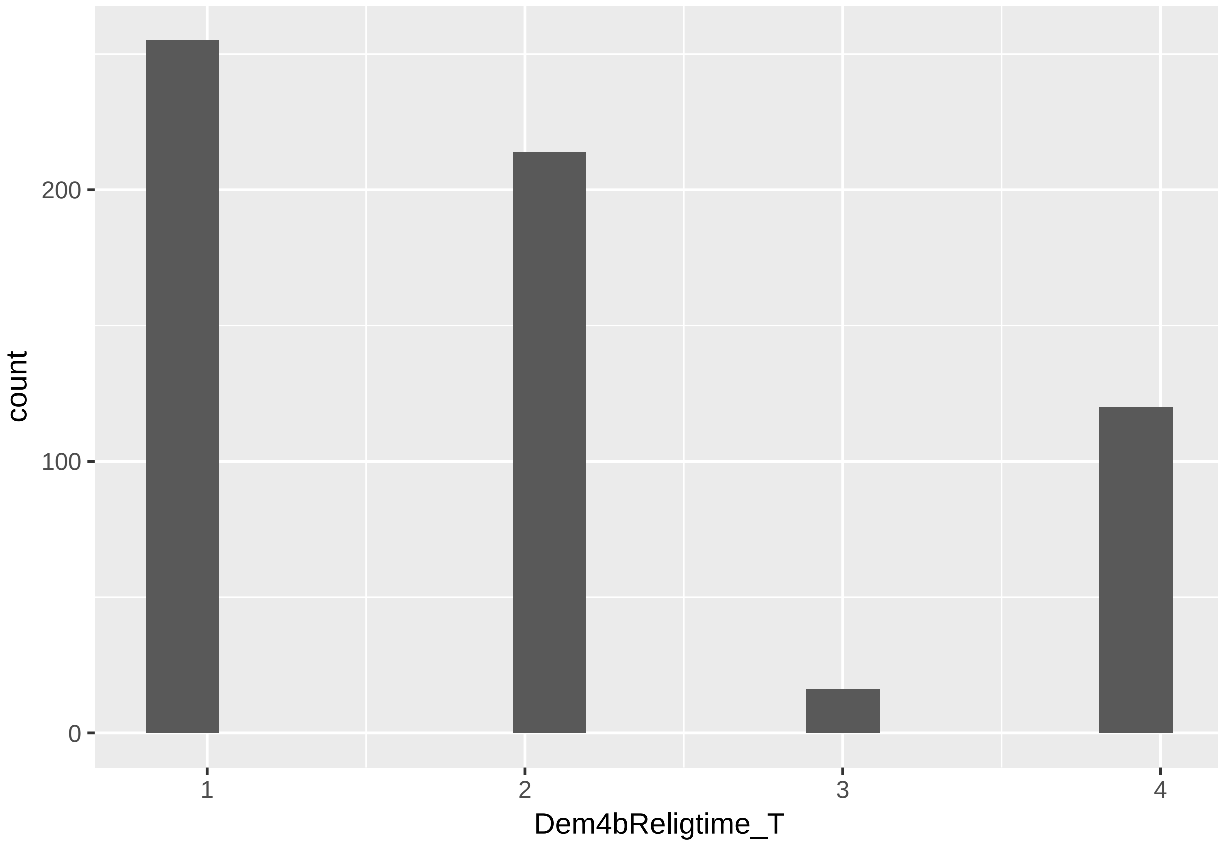

```
## Warning: Removed 5 rows containing non-finite values (stat_bin).
```




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




```
## Warning: Removed 4 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 should probably be reformulated in future surveys; 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 + interventionT + (1|city/ID), data=filtered)
m0 <- lmer(disMH_T ~ timePoint + interventionT + (1|ID), data=filtered)
m <- lmer(disMH_T ~ timePoint + interventionT + (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
```

```r
summary(disMH)
```

```
## Linear mixed model fit by REML t-tests use Satterthwaite approximations
##   to degrees of freedom [lmerMod]
## Formula: disMH_T ~ timePoint + interventionT + (1 | ID)
##    Data: filtered
##
## REML criterion at convergence: 2268.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3291 -0.5783 -0.0730  0.5678  3.4889
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.7996   0.8942
##  Residual             1.8750   1.3693
## Number of obs: 605, groups:  ID, 203
##
## Fixed effects:
##                            Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                 4.85544    0.11503 510.20000  42.211   <2e-16
## timePoint2                 -0.03333    0.17202 453.40000  -0.194    0.846
## timePoint3                 -0.15966    0.25425 504.40000  -0.628    0.530
## interventionTIntervention  -0.33554    0.21437 542.00000  -1.565    0.118
##
## (Intercept)               ***
## timePoint2
## timePoint3
## interventionTIntervention
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.470
## timePoint3  -0.319  0.726
## intrvntnTIn  0.001 -0.608 -0.844
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: disMH_T
##                   Chisq Df Pr(>Chisq)
## (Intercept)   1781.7334  1     <2e-16 ***
## timePoint        0.5395  2     0.7636
## interventionT    2.4499  1     0.1175
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#mA <- clmm(disAttribNaturalT  ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(disAttribNaturalT  ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(disAttribNaturalT  ~ timePoint + interventionT + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
```

```r
# 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 + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  605  -619.17 1252.34 414(1634) 9.32e-04 6.0e+01
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 2.518    1.587
## Number of groups:  ID 203
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## timePoint2                   -0.3944     0.2753  -1.433  0.15190
## timePoint3                   -0.3727     0.4154  -0.897  0.36964
## interventionTIntervention    1.0237     0.3550   2.884  0.00393 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2  -2.8604     0.2608 -10.966
## 2|3  -1.9452     0.2297  -8.467
## 3|4  -0.3014     0.2000  -1.507
## (4 observations deleted due to missingness)
```

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

```
## Analysis of Deviance Table (Type II tests)
##
## Response: disAttribNaturalT
##               LR Chisq Df Pr(>Chisq)
## timePoint       2.0865  2   0.352310
## interventionT   8.4930  1   0.003565 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#mA <- clmm(disAttribGodT ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(disAttribGodT ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(disAttribGodT ~ timePoint + interventionT + (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 + interventionT + (1 | ID)
## data:    filtered
```

```
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  604  -556.66 1127.32 419(2098) 1.20e-04 1.2e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 6.409    2.532
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                  -0.4698     0.3294  -1.426    0.154
## timePoint3                  -0.6898     0.4816  -1.432    0.152
## interventionTIntervention  -0.4166     0.4213  -0.989    0.323
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2   0.5694     0.2704   2.106
## 2|3   1.1994     0.2783   4.310
## 3|4   2.6297     0.3072   8.560
## (5 observations deleted due to missingness)
```

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

```
## Analysis of Deviance Table (Type II tests)
##
## Response: disAttribGodT
##               LR Chisq Df Pr(>Chisq)
## timePoint       2.2694  2     0.3215
## interventionT   0.9830  1     0.3215
```

```
#mA <- clmm(disAttribKarmaT  ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(disAttribKarmaT  ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(disAttribKarmaT  ~ timePoint + interventionT + (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 + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC    niter     max.grad cond.H
##  logit flexible  602  -427.59 869.19 333(2564) 1.32e-04 1.5e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 3.552    1.885
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                   0.5181     0.3353   1.545   0.1224
```

```
## timePoint3                  1.2835     0.5298   2.422   0.0154 *
## interventionTIntervention  -1.2186     0.4550  -2.678   0.0074 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2   2.0287     0.2934   6.916
## 2|3   2.5793     0.3119   8.270
## 3|4   4.6127     0.4034  11.434
## (7 observations deleted due to missingness)
```

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

```
## Analysis of Deviance Table (Type II tests)
##
## Response: disAttribKarmaT
##               LR Chisq Df Pr(>Chisq)
## timePoint       6.1013  2   0.047328 *
## interventionT   7.4675  1   0.006282 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#linear dis prep self perception
#mA <- clmm(disPrepSelfPerceptT  ~ timePoint + interventionT + (1|city/ID), data=filtered)
#m0 <- clmm(disPrepSelfPerceptT ~ timePoint + interventionT + (1|ID), data=filtered)
m0 <- lmer(disPrepSelfPerceptT ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(disPrepSelfPerceptT ~ timePoint + interventionT + (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 + interventionT + (1 | ID)
##    Data: filtered
##
## REML criterion at convergence: 1881.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.0081 -0.4880  0.0095  0.6049  1.8106
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 0.3161   0.5622
##  Residual             1.0453   1.0224
## Number of obs: 605, groups:  ID, 203
##
## Fixed effects:
##                            Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                 5.95561    0.08207 544.40000  72.563   <2e-16
## timePoint2                  0.20617    0.12760 464.10000   1.616   0.1068
## timePoint3                  0.44877    0.18748 521.10000   2.394   0.0170
```

```
## interventionTIntervention   0.25957    0.15730 561.30000   1.650   0.0995
##
## (Intercept)               ***
## timePoint2
## timePoint3                *
## interventionTIntervention .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.495
## timePoint3  -0.337  0.722
## intrvntnTIn  0.001 -0.602 -0.840
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: disPrepSelfPerceptT
##                   Chisq Df Pr(>Chisq)
## (Intercept)   5265.3962  1    < 2e-16 ***
## timePoint        5.7557  2    0.05625 .
## interventionT    2.7229  1    0.09892 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: copingPuja_T ~ timePoint + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  605  -590.14 1194.27 576(3974) 4.50e+00 2.0e+03
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 5.676    2.382
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                 0.048324   0.003326  14.529  < 2e-16 ***
## timePoint3                -0.015857   0.003327  -4.767 1.87e-06 ***
## interventionTIntervention -0.142754   0.003319 -43.006  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Threshold coefficients:
##     Estimate Std. Error  z value
## 1|2 0.453560   0.146029    3.106
## 2|3 2.793566   0.003318  841.948
## 3|4 4.237835   0.003332 1271.846
## (4 observations deleted due to missingness)
```

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

```
## Analysis of Deviance Table (Type II tests)
##
## Response: copingPuja_T
##                LR Chisq Df Pr(>Chisq)
## timePoint     0.084062  2     0.9588
## interventionT 0.137674  1     0.7106
```

```r
#mA <- clmm(copingCalming_T ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(copingCalming_T ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(copingCalming_T  ~ timePoint + interventionT + (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 + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  604  -652.32 1318.63 369(1110) 6.09e-05 4.0e+01
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 1.313    1.146
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                  0.10445    0.27193   0.384    0.701
## timePoint3                  0.06431    0.37357   0.172    0.863
## interventionTIntervention  1.42658    0.31601   4.514 6.35e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2   0.1207     0.1751    0.69
## 2|3   2.7128     0.2268   11.96
## 3|4   4.4008     0.3044   14.46
## (5 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       0.1847  2     0.9118
## interventionT  20.8386  1  4.997e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#mA <- clmm(copingSubuse_T  ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(copingSubuse_T  ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(copingSubuse_T   ~ timePoint + interventionT + (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 + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC    niter     max.grad cond.H
##  logit flexible  604  -262.43 538.87 323(1930) 4.81e-05 4.4e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 40.28    6.346
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                  -1.1441     0.5231  -2.187   0.0287 *
## timePoint3                  -1.4293     0.8243  -1.734   0.0829 .
## interventionTIntervention   0.2595     0.6942   0.374   0.7085
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2   5.8369     0.7769   7.513
## 2|3  10.0417     1.0369   9.685
## 3|4  10.7859     1.0755  10.029
## (5 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       5.2449  2    0.07262 .
## interventionT   0.1398  1    0.70850
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#mA <- clmm(chronicStressorsT ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(chronicStressorsT ~ timePoint + interventionT + (1|ID), data=filtered)
#m <- clmm(chronicStressorsT ~ timePoint + interventionT + (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 + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  604  -573.60 1161.20 444(2964) 3.82e-01 5.6e+01
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 3.839    1.959
## Number of groups:  ID 203
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## timePoint2                 -0.53922    0.29459  -1.830   0.0672 .
## timePoint3                 -0.93764    0.43259  -2.168   0.0302 *
## interventionTIntervention   0.01797    0.36438   0.049   0.9607
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 0|1  0.08722    0.22095   0.395
## 1|2  2.20083    0.25874   8.506
## 2|3  4.46726    0.37686  11.854
## (5 observations deleted due to missingness)
```

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

```
## Analysis of Deviance Table (Type II tests)
##
## Response: chronicStressorsT
##               LR Chisq Df Pr(>Chisq)
## timePoint       4.8673  2    0.08772 .
## interventionT   0.0006  1    0.98069
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
distress <- glmer(distressT ~ timePoint + interventionT + (1|ID), data=filtered, family = binomial)
summary(distress)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: distressT ~ timePoint + interventionT + (1 | ID)
##    Data: filtered
```

```
##
##      AIC      BIC   logLik deviance df.resid
##    526.5    548.6   -258.3    516.5      599
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0681 -0.2908 -0.2151 -0.2006  2.3078
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 2.929    1.712
## Number of obs: 604, groups:  ID, 203
##
## Fixed effects:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -1.9972     0.3127  -6.387 1.69e-10 ***
## timePoint2                  -0.6025     0.3945  -1.527    0.127
## timePoint3                  -0.9160     0.5845  -1.567    0.117
## interventionTIntervention    0.1913     0.4924   0.388    0.698
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.270
## timePoint3  -0.168  0.723
## intrvntnTIn  0.005 -0.635 -0.843
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: distressT
##                  Chisq Df Pr(>Chisq)
## (Intercept)    40.7939  1  1.692e-10 ***
## timePoint       2.7816  2     0.2489
## interventionT  0.1509  1     0.6977
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
mA <- glmer(HelpGivingMentalT ~ timePoint + interventionT + (1|city/ID), data = filtered, family = "bin
m0 <- glmer(HelpGivingMentalT ~ timePoint + interventionT + (1|ID), data = filtered, family = "binomial
anova(mA, m0)
```

```
## Data: filtered
## Models:
## m0: HelpGivingMentalT ~ timePoint + interventionT + (1 | ID)
## mA: HelpGivingMentalT ~ timePoint + interventionT + (1 | city/ID)
##    Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## m0  5 78.159 100.19 -34.079   68.159
## mA  6 80.159 106.59 -34.079   68.159     0      1     0.9988
```

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

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: HelpGivingMentalT ~ timePoint + interventionT + (1 | ID)
##    Data: filtered
##
##      AIC      BIC   logLik deviance df.resid
##     78.2    100.2    -34.1     68.2      600
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -11.3038   0.0009   0.0065   0.0065   1.2070
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 92.9     9.638
## Number of obs: 605, groups:  ID, 203
##
## Fixed effects:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  10.067      1.783   5.646 1.64e-08 ***
## timePoint2                   -1.223      1.241  -0.986    0.324
## timePoint3                  -28.181     44.127  -0.639    0.523
## interventionTIntervention   32.184     44.127   0.729    0.466
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.516
## timePoint3   0.003  0.003
## intrvntnTIn  0.003  0.003 -0.999
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: HelpGivingMentalT
##                 Chisq Df Pr(>Chisq)
## (Intercept)   31.8793  1  1.641e-08 ***
## timePoint      1.3761  2     0.5026
## interventionT  0.5320  1     0.4658
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
mA <- glmer(HelpGivingDisT ~ timePoint + interventionT + (1|city/ID), data = filtered, family = "binomia
m0 <- glmer(HelpGivingDisT ~ timePoint + interventionT + (1|ID), data = filtered, family = "binomial")
anova(mA, m0)
```

```
## Data: filtered
## Models:
## m0: HelpGivingDisT ~ timePoint + interventionT + (1 | ID)
## mA: HelpGivingDisT ~ timePoint + interventionT + (1 | city/ID)
##    Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## m0  5 62.395 84.421 -26.198   52.395
```

```
## mA   6 64.395 90.826 -26.198   52.395     0      1          1
```

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

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: HelpGivingDisT ~ timePoint + interventionT + (1 | ID)
##    Data: filtered
##
##      AIC      BIC   logLik deviance df.resid
##     62.4     84.4    -26.2     52.4      600
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.4345  0.0006  0.0045  0.0045  2.0896
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 113.5    10.66
## Number of obs: 605, groups:  ID, 203
##
## Fixed effects:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   10.810      2.246   4.812 1.49e-06 ***
## timePoint2                    -1.455      1.640  -0.887   0.3750
## timePoint3                   -96.711     42.951  -2.252   0.0243 *
## interventionTIntervention  100.652     42.951   2.343   0.0191 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) tmPnt2 tmPnt3
## timePoint2  -0.626
## timePoint3   0.004  0.001
## intrvntnTIn  0.004  0.001 -0.999
```

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

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: HelpGivingDisT
##                 Chisq Df Pr(>Chisq)
## (Intercept)   23.1564  1  1.493e-06 ***
## timePoint      5.8515  2    0.05362 .
## interventionT  5.4917  1    0.01911 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#mA <- clmm(Dem4bReligtime_T ~ timePoint + interventionT + (1|city/ID), data=filtered)
m0 <- clmm(Dem4bReligtime_T ~ timePoint + interventionT + (1|ID), data=filtered)
```

```
## Warning in update.uC(rho): Non finite negative log-likelihood
##   at iteration 59
```

```r
#m <- clmm(Dem4bReligtime_T ~ timePoint + interventionT + (1|city), data=filtered)
#exactRLRT(m=m, mA=mA, m0=m0)
# tells us the city random effect is not needed; we'll take m0
relig_time <- m0
summary(relig_time)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: Dem4bReligtime_T ~ timePoint + interventionT + (1 | ID)
## data:    filtered
##
##  link  threshold nobs logLik  AIC     niter     max.grad cond.H
##  logit flexible  605  -596.32 1206.65 368(1823) 4.00e-05 1.5e+02
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 7.305    2.703
## Number of groups:  ID 203
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## timePoint2                  0.4373     0.3031   1.443    0.149
## timePoint3                  0.3144     0.4425   0.711    0.477
## interventionTIntervention   0.4896     0.3777   1.296    0.195
##
## Threshold coefficients:
##     Estimate Std. Error z value
## 1|2  -0.1356     0.2664  -0.509
## 2|3   2.9745     0.3112   9.558
## 3|4   3.2698     0.3176  10.296
## (4 observations deleted due to missingness)
```

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

```
## Warning in update.uC(rho): Non finite negative log-likelihood
##   at iteration 45

## Warning in update.uC(rho): Non finite negative log-likelihood
##   at iteration 52

## Analysis of Deviance Table (Type II tests)
##
## Response: Dem4bReligtime_T
##               LR Chisq Df Pr(>Chisq)
## timePoint       2.3975  2     0.3016
## interventionT   1.6845  1     0.1943
```

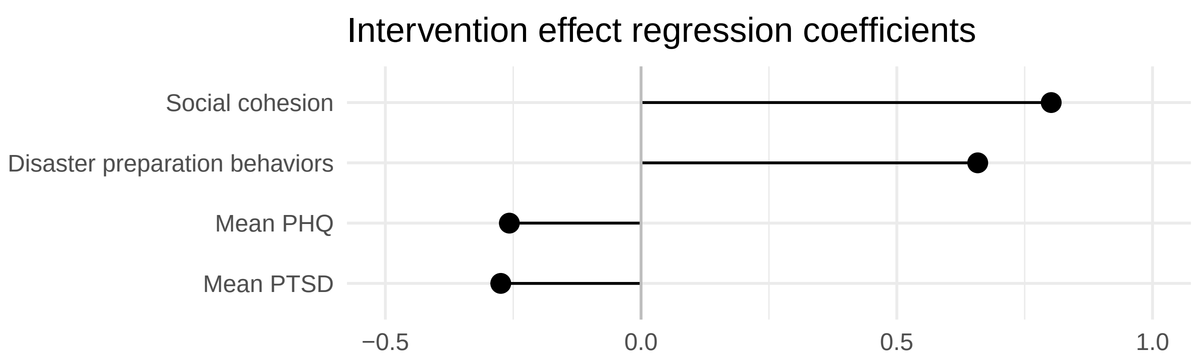
Summary plots

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

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

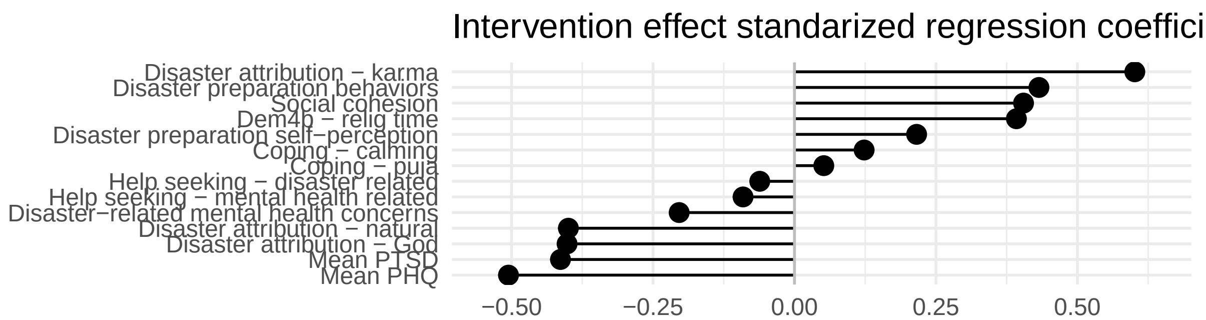
```r
estimates[1] <- summary(disPrep)$coef[,'Estimate'][4]
estimates[1] <- exp(estimates[1]) / (1 + exp(estimates[1]))
estimates[2] <- summary(phq)$coef[,'Estimate'][4]
estimates[3] <- summary(ptsd)$coef[,'Estimate'][4]
estimates[4] <- summary(soc_coh)$coef[,'Estimate'][4]
estimates[5] <- summary(help_seeking_mental)$coef[,'Estimate'][4]
estimates[6] <- summary(help_seeking_dis)$coef[,'Estimate'][4]
estimates[7] <- summary(help_giving_mental)$coef[,'Estimate'][4]
estimates[8] <- summary(help_giving_dis)$coef[,'Estimate'][4]
estimates[9] <- summary(disMH)$coef[,'Estimate'][4]
estimates[10] <- summary(disAttribNatural)$coef[,'Estimate'][4]
estimates[11] <- summary(disAttribGod)$coef[,'Estimate'][4]
estimates[12] <- summary(disAttribKarma)$coef[,'Estimate'][4]
estimates[13] <- summary(disPrep_selfPercept)$coef[,'Estimate'][4]
estimates[14] <- summary(copingPuja)$coef[,'Estimate'][4]
estimates[15] <- summary(copingCalming)$coef[,'Estimate'][4]
estimates[16] <- summary(copingSubuse)$coef[,'Estimate'][4]
estimates[17] <- summary(relig_time)$coef[,'Estimate'][4]
#estimates[15] <- summary(distress)$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(as.numeric(filtered$HelpSeekingMentalT), na.rm = TRUE)
sds[6] <- sd(as.numeric(filtered$HelpSeekingDisT), na.rm = TRUE)
sds[7] <- sd(filtered$HelpGivingMentalT, na.rm = TRUE)
sds[8] <- sd(filtered$HelpGivingDisT, na.rm = TRUE)
sds[9] <- sd(filtered$disMH_T, na.rm = TRUE)
sds[10] <- sd(as.numeric(filtered$disAttribNaturalT), na.rm = TRUE)
sds[11] <- sd(as.numeric(filtered$disAttribGodT), na.rm = TRUE)
sds[12] <- sd(as.numeric(filtered$disAttribKarmaT), na.rm = TRUE)
sds[13] <- sd(filtered$disPrepSelfPerceptT, na.rm = TRUE)
sds[14] <- sd(as.numeric(filtered$copingPuja_T), na.rm = TRUE)
sds[15] <- sd(as.numeric(filtered$copingCalming_T), na.rm = TRUE)
sds[16] <- sd(as.numeric(filtered$copingSubuse_T), na.rm = TRUE)
sds[17] <- sd(as.numeric(filtered$Dem4bReligtime_T), na.rm = TRUE)
#sds[15] <- sd(filtered$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") +
```

```r
  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).

```r
ggplot(effects[!(effects$dvs %in% c("Help giving - mental health related","Help giving - disaster relat
  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.

```
DV_names <-
c('Disaster preparation behaviors', 'Disaster prep 5 items', 'Mean PHQ', 'Mean PTSD', 'Social cohesion'

models <- list(disPrepLinear, disPrepExcludedItemsLinear, phq, ptsd, soc_coh, help_seeking_mental, help

texreg(models[1:4], type = "html",  digits = 3, bold = .05, booktabs = TRUE, sideways = TRUE, use.packa
```

```
coefs <- sapply(models, function(x) coef(summary(x))['interventionTIntervention',1])
se <- sapply(models, function(x) coef(summary(x))['interventionTIntervention',2])
p <- sapply(models, function(x) coef(summary(x))['interventionTIntervention', ncol(coef(summary(x)))])
d <- vector(mode="numeric", length=length(coefs))
for(i in 1:length(coefs)){
  if(class(models[[i]]) == "merModLmerTest") {
    y <- getME(models[[i]], name = 'y')
    X <- getME(models[[i]], name = 'X')
    d[i] <- coefs[i] / sd(y[X[,'timePoint2'] == 0 & X[,'timePoint3'] == 0])
  }
  else {
    d[i] <- NA
  }
```

	Disaster preparation behaviors	Disaster prep 5 items	Mean PHQ	Mean PTSD
(Constant)	**4.455*****	**3.469*****	**1.774*****	**1.965*****
	(0.337)	(0.157)	(0.034)	(0.046)
Time point = 2	**0.463*****	**0.292****	**−0.139****	**−0.125***
	(0.138)	(0.112)	(0.043)	(0.050)
Time point = 3	**0.836*****	**0.461****	**−0.135***	−0.079
	(0.211)	(0.171)	(0.065)	(0.076)
Intervention	**0.748*****	**0.590*****	**−0.258*****	**−0.274*****
	(0.182)	(0.148)	(0.055)	(0.065)
Num. obs.	605	605	605	605
Var: ID:city (Intercept)	0.556	0.375		
Var: city (Intercept)	0.210	0.038		
Var: Residual	1.122	0.749	0.116	0.152
Var: ID (Intercept)			0.116	0.270

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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).

```
}
coef_df <- data.frame(row.names = DV_names, Coefficient = coefs, 'Std error' = se, 'P value' = p, 'Cohe
```

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

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:30:41 2018

	Coefficient	Std.error	P.value	Cohens.d
Disaster preparation behaviors	0.75	0.18	0.0000	0.49
Disaster prep 5 items	0.59	0.15	0.0001	0.47
Mean PHQ	-0.26	0.06	0.0000	-0.49
Mean PTSD	-0.27	0.06	0.0000	-0.39
Social cohesion	0.80	0.28	0.0049	0.40
Help seeking - mental health related	0.76	0.30	0.0116	
Help seeking - disaster related	0.69	0.31	0.0262	
Help giving - mental health related	32.18	44.13	0.4658	
Help giving - disaster related	100.65	42.95	0.0191	
Disaster-related mental health concerns	-0.34	0.21	0.1181	-0.19
Disaster attribution - natural	1.02	0.35	0.0039	
Disaster attribution - God	-0.42	0.42	0.3227	
Disaster attribution - karma	-1.22	0.46	0.0074	
Disaster preparation self-perception	0.26	0.16	0.0995	0.21
Coping - puja	-0.14	0.00	0.0000	
Coping - calming	1.43	0.32	0.0000	
Coping - substance use	0.26	0.69	0.7085	
Dem4b - relig time	0.49	0.38	0.1949	

Table 5: Intervention effect coefficients

```
contrasts_1to2_untrans <- data.frame()
contrasts_1to3_untrans <- data.frame()
contrasts_1to2_backtrans <- data.frame()
contrasts_1to3_backtrans <- data.frame()

for(mod in models) {
  MM <- lsmeans::lsmeans(update(mod, . ~ timePoint * city + (1|ID)), ~ timePoint * city)
  contrast_result_untrans <- summary(pairs(MM), adjust = "none")
  contrast_result_backtrans <- summary(pairs(MM), adjust = "none", type = "response")
  if(dim(contrasts_1to2_backtrans)[1] == 0) {
    contrasts_1to2_untrans <- contrast_result_untrans[1,]
    contrasts_1to3_untrans <- contrast_result_untrans[2,]
    contrasts_1to2_backtrans <- contrast_result_backtrans[1,]
    contrasts_1to3_backtrans <- contrast_result_backtrans[2,]
  }
  else {
    contrasts_1to2_untrans <- rbind(contrasts_1to2_untrans, setNames(contrast_result_untrans[1,], names
    contrasts_1to3_untrans <- rbind(contrasts_1to3_untrans, setNames(contrast_result_untrans[2,], names
    contrasts_1to2_backtrans <- rbind(contrasts_1to2_backtrans, setNames(contrast_result_backtrans[1,],
    contrasts_1to3_backtrans <- rbind(contrasts_1to3_backtrans, setNames(contrast_result_backtrans[2,],
  }
}
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : unable to evaluate scaled gradient
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge: degenerate Hessian with 1 negative
## eigenvalues

## Warning in vcov.merMod(object, correlation = FALSE): variance-covariance matrix computed from finite-
## not positive definite or contains NA values: falling back to var-cov estimated from RX

## Warning in update.uC(rho): Non finite negative log-likelihood
##   at iteration 73
```

```
row.names(contrasts_1to2_untrans) <- DV_names
row.names(contrasts_1to3_untrans) <- DV_names
row.names(contrasts_1to2_backtrans) <- DV_names
row.names(contrasts_1to3_backtrans) <- DV_names
```

```
print(xtable(contrasts_1to2_untrans, auto = TRUE, caption = "Link-scale within subject contrasts for ti
```

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:18 2018

	contrast	estimate	SE	df	t.ratio	p.value
Disaster preparation behaviors	1,Chhaling - 2,Chhaling	-1.19	0.15	398.53	-7.882	<.0001
Disaster prep 5 items	1,Chhaling - 2,Chhaling	-0.86	0.12	398.21	-6.923	<.0001
Mean PHQ	1,Chhaling - 2,Chhaling	0.38	0.05	396.39	7.914	<.0001
Mean PTSD	1,Chhaling - 2,Chhaling	0.33	0.05	396.15	6.032	<.0001
Social cohesion	1,Chhaling - 2,Chhaling	-0.83	0.24	396.85	-3.487	0.0005
Help seeking - mental health related	1,Chhaling - 2,Chhaling	-0.56	0.27		-2.092	0.0364
Help seeking - disaster related	1,Chhaling - 2,Chhaling	-0.63	0.27		-2.364	0.0181
Help giving - mental health related	1,Chhaling - 2,Chhaling	-636.60	180.32		-3.530	0.0004
Help giving - disaster related	1,Chhaling - 2,Chhaling	-56.06	6770388.77		-0.000	1.0000
Disaster-related mental health concerns	1,Chhaling - 2,Chhaling	0.17	0.19	395.50	0.891	0.3734
Disaster attribution - natural	1,Chhaling - 2,Chhaling	-0.51	0.31		-1.616	0.1062
Disaster attribution - God	1,Chhaling - 2,Chhaling	0.96	0.34		2.790	0.0053
Disaster attribution - karma	1,Chhaling - 2,Chhaling	0.42	0.44		0.969	0.3325
Disaster preparation self-perception	1,Chhaling - 2,Chhaling	-0.37	0.15	399.41	-2.517	0.0122
Coping - puja	1,Chhaling - 2,Chhaling	-0.14	0.33		-0.430	0.6669
Coping - calming	1,Chhaling - 2,Chhaling	-1.48	0.29		-5.051	<.0001
Coping - substance use	1,Chhaling - 2,Chhaling	0.82	0.58		1.411	0.1581
Dem4b - relig time	1,Chhaling - 2,Chhaling	-0.75	0.33		-2.281	0.0225

Table 6: Link-scale within subject contrasts for time 1 to time 2 for intervention group

```
print(xtable(contrasts_1to3_untrans, auto = TRUE, caption = "Link-scale Within subject contrasts for ti
```

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:18 2018

```
print(xtable(contrasts_1to2_backtrans, auto = TRUE, caption = "Back-transformed response-scale within s
```

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```
print(xtable(contrasts_1to3_backtrans, auto = TRUE, caption = "Back-transformed response-scale within s
```

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:18 2018

Also, we'll output some descriptive statistics on demographic variables organized by city.

```
vars <- data %>% filter(timePoint == "1") %>% select(T1Dem1Age, T1Dem2Educ, T1Dem7Numchildren)
city <- data %>% filter(timePoint == "1") %>% select(city) %>% as.data.frame
vars$T1Dem7Numchildren <- as.numeric(vars$T1Dem7Numchildren)
```

	contrast	estimate	SE	df	t.ratio	p.value
Disaster preparation behaviors	1,Chhaling - 3,Chhaling	-1.57	0.15	399.39	-10.318	<.0001
Disaster prep 5 items	1,Chhaling - 3,Chhaling	-1.03	0.12	399.07	-8.267	<.0001
Mean PHQ	1,Chhaling - 3,Chhaling	0.35	0.05	397.00	7.158	<.0001
Mean PTSD	1,Chhaling - 3,Chhaling	0.19	0.05	396.55	3.473	0.0006
Social cohesion	1,Chhaling - 3,Chhaling	-0.54	0.24	397.80	-2.256	0.0246
Help seeking - mental health related	1,Chhaling - 3,Chhaling	-0.36	0.26		-1.353	0.1761
Help seeking - disaster related	1,Chhaling - 3,Chhaling	-0.36	0.26		-1.366	0.1718
Help giving - mental health related	1,Chhaling - 3,Chhaling	-149.40	45.22		-3.304	0.0010
Help giving - disaster related	1,Chhaling - 3,Chhaling	-2.21	1.91		-1.162	0.2452
Disaster-related mental health concerns	1,Chhaling - 3,Chhaling	0.19	0.20	396.41	0.980	0.3278
Disaster attribution - natural	1,Chhaling - 3,Chhaling	-0.40	0.31		-1.300	0.1936
Disaster attribution - God	1,Chhaling - 3,Chhaling	0.83	0.33		2.472	0.0134
Disaster attribution - karma	1,Chhaling - 3,Chhaling	-0.26	0.41		-0.631	0.5281
Disaster preparation self-perception	1,Chhaling - 3,Chhaling	-0.57	0.15	400.41	-3.885	0.0001
Coping - puja	1,Chhaling - 3,Chhaling	-0.06	0.34		-0.173	0.8625
Coping - calming	1,Chhaling - 3,Chhaling	-1.65	0.29		-5.597	<.0001
Coping - substance use	1,Chhaling - 3,Chhaling	1.16	0.62		1.880	0.0601
Dem4b - relig time	1,Chhaling - 3,Chhaling	-0.44	0.33		-1.339	0.1804

Table 7: Link-scale Within subject contrasts for time 1 to time 3 for intervention group

```
## Warning: NAs introduced by coercion
```

```
tableContinuous(vars = as.data.frame(vars), group = city[,1], stats = c('n', 'min', 'q1', 'median', 'mea
```

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:19 2018

Variable	Levels	n	Min	q_1	$\tilde{x}$	$\bar{x}$	q_3	Max
T1Dem1Age	Chhaling	119	18	30.00	39	39.85	47	72
	Tathali	119	18	26.00	35	37.30	48	68
	all	238	18	28.25	38	38.58	48	72
T1Dem2Educ	Chhaling	119	1	2.00	4	3.57	5	8
	Tathali	119	1	2.00	4	3.75	5	8
	all	238	1	2.00	4	3.66	5	8
T1Dem7Numchildren	Chhaling	119	0	1.00	2	2.24	3	8
	Tathali	117	0	1.00	2	1.92	3	8
	all	236	0	1.00	2	2.08	3	8

Table 10: Descriptive statistics

Now for the mental health variables by time point.

```
vars <- data %>% select(phqMean6_T, ptsdMean11_T, DisMH1Anxiousdep_T, DisMH2Avoid_T)
time <- data %>% select(timePoint) %>% as.data.frame
tableContinuous(vars = as.data.frame(vars), group = time[,1], stats = c('n', 'min', 'q1', 'median', 'mea
```

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:19 2018

Variable	Levels	n	Min	q_1	$\tilde{x}$	$\bar{x}$	q_3	Max
phqMean6_T	1	239	1	1.33	1.67	1.75	2.11	3.44
	2	230	1	1.11	1.33	1.51	1.78	3.33
	3	226	1	1.11	1.33	1.39	1.56	3.22
	all	695	1	1.11	1.44	1.55	1.89	3.44
ptsdMean11_T	1	239	1	1.41	1.82	1.91	2.27	4.53
	2	230	1	1.24	1.50	1.68	1.94	4.53
	3	226	1	1.18	1.47	1.60	1.88	3.88
	all	695	1	1.24	1.59	1.73	2.06	4.53
DisMH1Anxiousdep_T	1	238	1	2.00	2.00	2.53	3.00	5.00
	2	230	1	2.00	2.00	2.28	3.00	5.00
	3	226	1	2.00	2.00	2.17	3.00	5.00
	all	694	1	2.00	2.00	2.33	3.00	5.00
DisMH2Avoid_T	1	238	1	2.00	2.00	2.37	3.00	5.00
	2	230	1	2.00	2.00	2.33	3.00	5.00
	3	226	1	1.00	2.00	2.19	3.00	5.00
	all	694	1	2.00	2.00	2.30	3.00	5.00

T1Dem2Educ	Chhaling	98	1	2	4.00	3.56	5	8
	Tathali	104	1	2	4.00	3.75	5	8
	all	202	1	2	4.00	3.66	5	8
T1Dem7Numchildren	Chhaling	97	0	2	2.00	2.21	3	7
	Tathali	102	0	1	2.00	1.95	3	8
	all	199	0	1	2.00	2.08	3	8

Table 12: Descriptive statistics

```
vars <- filtered %>% select(phqMean6_T, ptsdMean11_T, DisMH1Anxiousdep_T, DisMH2Avoid_T)
time <- filtered %>% select(timePoint) %>% as.data.frame
tableContinuous(vars = as.data.frame(vars), group = time[,1], stats = c('n', 'min', 'q1', 'median', 'mea
```

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:19 2018

Variable	**Levels**	**n**	**Min**	$\mathbf{q_1}$	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	$\mathbf{q_3}$	**Max**
phqMean6_T	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	605	1	1.11	1.44	1.55	1.89	3.44
ptsdMean11_T	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	605	1	1.24	1.59	1.76	2.12	4.53
DisMH1Anxiousdep_T	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	605	1	2.00	2.00	2.36	3.00	5.00
DisMH2Avoid_T	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	605	1	2.00	2.00	2.26	3.00	5.00

Table 13: Descriptive statistics

% 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**	$\mathbf{q_1}$	$\widetilde{\mathbf{x}}$	$\bar{\mathbf{x}}$	$\mathbf{q_3}$	**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 14: Descriptive statistics

Then also for the qualitative data regarding new trauma experiences.

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

	contrast	estimate	SE	df	t.ratio	p.value
Disaster preparation behaviors	1,Chhaling - 2,Chhaling	-1.19	0.15	398.53	-7.882	<.0001
Disaster prep 5 items	1,Chhaling - 2,Chhaling	-0.86	0.12	398.21	-6.923	<.0001
Mean PHQ	1,Chhaling - 2,Chhaling	0.38	0.05	396.39	7.914	<.0001
Mean PTSD	1,Chhaling - 2,Chhaling	0.33	0.05	396.15	6.032	<.0001
Social cohesion	1,Chhaling - 2,Chhaling	-0.83	0.24	396.85	-3.487	0.0005
Help seeking - mental health related	1,Chhaling - 2,Chhaling	-0.56	0.27		-2.092	0.0364
Help seeking - disaster related	1,Chhaling - 2,Chhaling	-0.63	0.27		-2.364	0.0181
Help giving - mental health related	1,Chhaling - 2,Chhaling	0.00	0.00		-3.530	0.0004
Help giving - disaster related	1,Chhaling - 2,Chhaling	0.00	0.00		-0.000	1.0000
Disaster-related mental health concerns	1,Chhaling - 2,Chhaling	0.17	0.19	395.50	0.891	0.3734
Disaster attribution - natural	1,Chhaling - 2,Chhaling	-0.51	0.31		-1.616	0.1062
Disaster attribution - God	1,Chhaling - 2,Chhaling	0.96	0.34		2.790	0.0053
Disaster attribution - karma	1,Chhaling - 2,Chhaling	0.42	0.44		0.969	0.3325
Disaster preparation self-perception	1,Chhaling - 2,Chhaling	-0.37	0.15	399.41	-2.517	0.0122
Coping - puja	1,Chhaling - 2,Chhaling	-0.14	0.33		-0.430	0.6669
Coping - calming	1,Chhaling - 2,Chhaling	-1.48	0.29		-5.051	<.0001
Coping - substance use	1,Chhaling - 2,Chhaling	0.82	0.58		1.411	0.1581
Dem4b - relig time	1,Chhaling - 2,Chhaling	-0.75	0.33		-2.281	0.0225

Table 8: Back-transformed response-scale within subject contrasts for time 1 to time 2 for intervention group

% latex table generated in R 3.4.3 by xtable 1.8-2 package % Mon Mar 05 16:31:19 2018

Variable	**Levels**	**n**	%
T3NewTrauma	0	218	96.5
	1	8	3.5
	all	226	100.0
T3NewTraumaopen	0	232	96.7
	aja bholi srimati lai dindinai behosh bhai raheko xa yo 14 dinma 5,6 patak behosh bhaisakyo .	1	0.4
	baccha chadeko gadi palteko	1	0.4
	birami bhaye	1	0.4
	birami ko karan le	1	0.4
	chhorako bahira padna gani kurama	1	0.4
	gharayasi ghatanale	1	0.4
	ghareru samasyaharu	1	0.4
	srimanlai kukurle toker afulai akdamai tanab bhayeko.	1	0.4
	all	240	100.0

Table 15:

	contrast	estimate	SE	df	t.ratio	p.value
Disaster preparation behaviors	1,Chhaling - 3,Chhaling	-1.57	0.15	399.39	-10.318	<.0001
Disaster prep 5 items	1,Chhaling - 3,Chhaling	-1.03	0.12	399.07	-8.267	<.0001
Mean PHQ	1,Chhaling - 3,Chhaling	0.35	0.05	397.00	7.158	<.0001
Mean PTSD	1,Chhaling - 3,Chhaling	0.19	0.05	396.55	3.473	0.0006
Social cohesion	1,Chhaling - 3,Chhaling	-0.54	0.24	397.80	-2.256	0.0246
Help seeking - mental health related	1,Chhaling - 3,Chhaling	-0.36	0.26		-1.353	0.1761
Help seeking - disaster related	1,Chhaling - 3,Chhaling	-0.36	0.26		-1.366	0.1718
Help giving - mental health related	1,Chhaling - 3,Chhaling	0.00	0.00		-3.304	0.0010
Help giving - disaster related	1,Chhaling - 3,Chhaling	0.11	0.21		-1.162	0.2452
Disaster-related mental health concerns	1,Chhaling - 3,Chhaling	0.19	0.20	396.41	0.980	0.3278
Disaster attribution - natural	1,Chhaling - 3,Chhaling	-0.40	0.31		-1.300	0.1936
Disaster attribution - God	1,Chhaling - 3,Chhaling	0.83	0.33		2.472	0.0134
Disaster attribution - karma	1,Chhaling - 3,Chhaling	-0.26	0.41		-0.631	0.5281
Disaster preparation self-perception	1,Chhaling - 3,Chhaling	-0.57	0.15	400.41	-3.885	0.0001
Coping - puja	1,Chhaling - 3,Chhaling	-0.06	0.34		-0.173	0.8625
Coping - calming	1,Chhaling - 3,Chhaling	-1.65	0.29		-5.597	<.0001
Coping - substance use	1,Chhaling - 3,Chhaling	1.16	0.62		1.880	0.0601
Dem4b - relig time	1,Chhaling - 3,Chhaling	-0.44	0.33		-1.339	0.1804

Table 9: Back-transformed response-scale within subject contrasts for time 1 to time 3 for intervention group