## **PTSD Meta-Analysis**

### Table of contents

### Load Data and R Packages

### R Packages we will use:

```
library(haven)
library(tidyverse)
library(metafor)
library(brms)
library(lme4)
library(gt)
```

### **Load Data**

Note that I've changed some of the raw data that is incorrect.

Note that for study 1, the number of men and women (115, 134) adds up 249, but the total is listed as 252, which is due to missing gender information for 3 individuals in the original source.

Presumably this the same issue with study 15 (Pat-Horenczyk).

### Data Description

- participants Number of Participants
- male Number of Males
- mpercent Percentage of males in the sample
- Female Number of Females
- fpercent Percentage of females in the sample

 $\bullet\,$  age - mean age of sample participants

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12	952NA54. <b>N</b> OA45. <b>36.83.N</b> OANAO	_	oMelt0	6	NANANA NANANANA2	13 21 5	6
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13	55128 <b>4</b> 51. <b>267</b> 48. <b>56.72.20.28.7</b>		d@ke110	57	NANANA NANANANA2	13 21 7	7
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14	1468/A47.40A52.66.5080/ANA0	NAHTOk2a	in <b>@</b> so <b>k1i</b>	n9a	60.2NANA 13.3NANANANA1	11 17 8	9
15	482NA46. <b>N</b> 0A47. <b>76.2</b> 90NANA1	2.0 <b>0</b> ClsrAdel	Pat2	3	NANANA NANANANA3	$12\ 18\ 3$	3
		PTS	Horen	ıczy	k,		
16	23370 30. <b>06</b> 369. <b>66.49.</b> NOAN <i>A</i> 0	NAUC <b>II</b> sr <b>A</b> alel	Sha <b>2</b> he	een	NANANA NANANANA3	$11\ 16\ 5$	3
		PTS					

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### **Compute Additional Variables**

Add missing count data using the extracted percentages

Reformatted percentages so they're from 0-1 and not 0-100

Created mean-centered age variable

Fixed error on the Harb study where males were not measured in their PTSD

```
# df$male_plus_female_percent = df$mpercent + df$fpercent
df$mpercent = df$mpercent/100
df$fpercent = df$fpercent/100
df$ptsd
          = df ptsd/100
df$mptsd
            = df \pm d/100
df$fptsd
             = df$fptsd/100
df$authors = as.character(df$authors)
df$aftermath = df$aftermath/12
df$male[is.na(df$male)] = round(
 df$participants[is.na(df$male)]*df$mpercent[is.na(df$male)]
df$female[is.na(df$female)] = round(
 df$participants[is.na(df$female)]*df$fpercent[is.na(df$female)]
df$ptsd_n = round(df$ptsd*df$participants)
```

```
df$authors[df$authors == "Marroquin"] = "Rivera"
df$authors[grep("^Pat",df$authors)] = "Pat-Horenczyk"

df$war[df$authors == "El-Khodary"] = 1

table(df$aftermath, df$war, useNA = "always")
```

```
0 1 <NA>
0.08333333333333 0 1
0.25
             0 1
                   0
0.75
             0 1
                   0
0.8333333333333 0 1
                   0
             0 1
                   0
3.86
             0 1
4
             0 1
                   0
4.75
             0 1
                   0
             0 1
9
                   0
10
             0 2
                   0
<NA>
             9 0
                   0
```

```
df$measure[df$measure == "UCLA PTS"] = "UCLA-PTS"
df$measure_factor = factor(paste0("M",df$measures1))
df$qualityassessment_factor = factor(paste0("Quality Rating: ",df$qualityassessment))
harb_row = which(df$authors=="Harb")
df$participants[harb_row] = 40
df$male[harb_row]
                        = 0
df$mpercent[harb_row]
                        = 0
df$female[harb_row]
                        = 40
df$fpercent[harb_row]
                        = 1
df$mptsd[harb_row]
                        = NA
df$ptsd[harb_row]
                        = .90
df = df \%
```

```
# filter(!exclude) %>%
select("authors", "participants", "ptsd_n", everything()) %>%
mutate(
   age_centered = scale(age, center = TRUE, scale = FALSE),
   aftermath_centered = scale(aftermath, center = TRUE, scale = FALSE),
   quality_centered = scale(qualityassessment, center = TRUE, scale = TRUE)
)
```

### Cleaned Dataset

```
write.csv(df, file.path("data","cleaned_df.csv"))

df %>%
   rowid_to_column() %>%
   knitr::kable()
```

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```
1 Fa25:289115.4560.5B20'.3N5NA 0.75'00000310n7 75.42.38.36.35.29.46.B5.29 12187 7 M1Quality 0.50478790
                                                                      Ra0-425.97114344
                                                                      ing:
                                                                      7
Kaf
                                                                      Rat-
                                                                             2.03934313
                                                                      ing:
                                                                      1
3 Al4032462480.6115560.385565.6001.508.60530NASPIFS66 5 4 NANANANANANANANA 16194 4 M5Qu2.1318442857
                                                                             0.76727761
  Hadethe
                                                                      Rat-
                                                                      ing:
4 Bh7397397469.53239.41120941NSNAO NAPOIh42ia3 7 7.027NAO.016.26.51.3NA2 19246 7 M3Qu4s17NAO8507478790
                             5
                                                                      Rat-
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5 Ch235k 960.411350.58409.00X2N A 0.08333863316d9 NANANANANANANA 12219 9 McQuality 1.35283158
                                                                      Ra0-26.57114311
                                                                      ing:
                                                                      9
```

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El-10 <b>25</b> 49 <b>6</b> .4 <b>525</b> .51 <b>.30</b> .5 <b>N5N</b> A Khodary	1.0 <b>0008429.5</b> 6 Str	83.17 A88.88.14 AN AN AN A2	11177	•	lity 0.08076606 -4 <b>3</b> 5721413144
Fre <b>2242520.5860.4648.95.80.48</b> 0	00.19 <b>0083368</b> 7	NANANA28 <i>5</i> 77 MANA13.2	12237		=
Ha469 0 0.0000.0000.0000.000	NACRIES 1 3 Str	NANANANANANANA	12163	•	liN/A -665 <b>7</b> 1149129945
Ka <b>k36926</b> 230.533800 Al 6.33839000 Al	9.0 <b>001919518</b> a1 9	NANANANANANANA	16187	9 MiQui Rating: 9	·
) La <b>2</b> 8 B <b>4 7</b> 1 <b>20</b> 48 <b>490</b> 45 <b>1.5 (5.0 NON</b> <i>A</i>	0.8 <b>333323</b> 8 6 RI	NANANANANANANA	12156	•	dity 0.08076606 -6 <b>2391143</b> 11
1 Rivio 243 40 0.3502 2.6 D 7 56.1 N 3 N A	N <b>AP (CLeB</b> on <b>hB</b> ifa C	NANANANANANANANA	12177	•	lliNyA0.50478790 -5557143
2 M <b>.952</b> 1972 <b>0</b> .5 <b>470</b> .4 <b>538.3122</b> N <i>A</i> )	N <b>AE</b> Co <b>2</b> g <b>b</b> 06 R	NANANANANANANANA	13215	6 M1Qu2 Rating: 6	•
3 Ok <b>551</b> b0 <b>2</b> 8 <b>4</b> .5 <b>257</b> 0.4 <b>85.0.29.20</b> .2 <b>6</b> 7	<b>5.0110161130</b> 001110.7 R	NANANANANANANANA	13217	7 M1Qub Rating: 7	-
4 Osb <b>4673</b> 6930.47740.525000 <b>53</b> 0 A	NAHTIQ(2)ainle9	60.34 AN A13.39 AN AN AN A1	11178	-	liiNyA1.35283158 -1657143
5 Pa <b>4824</b> 22 <b>5</b> .4 <b>230</b> .4 <b>77029N0N A</b> Horenczyk	0.1 <b>66667</b> 2 3 PTS	NANANANANANANA	12183	•	.l <b>14</b> 942857 - 3.5 <b>5.79729</b> 945

```
16 Sh2B39370 0.3D669.6D669.9N6NAO NAUCI$rAel2 3 NANANANANANANAN 11165 3 M2QualiNyA
                             PTS
                                                                      Rat-675711493129945
                                                                      ing:
                                                                      3
17Shbb3736.4942.5030.2N6NAO NAUCCaAca2 7 7.1NANA16.6.5NANA1.02 13157 7 M2Qualin:A0.50478790
                             PTStr
                                                                      Rat-4357143
                                                                      ing:
                                                                      7
18 Th35560750.42000.55007.22NSN A 0.25000DA90.2 4 88 NANANANANANAN 15184 4 M2Qub.15042857
                             PTStr
                                                                      Rat- 3.4074746474247761
                                                                      ing:
                                                                      4
19 Uy$3026385.42305.57505.60120 A 4.75050020 1 9 NANANANANANANANA 12189 9 M1Qu3.1383028557283158
                                                                      Rat-
                                                                      ing:
                                                                      9
20 Yillml8z 43 0.3761 0.6B393.606.704.70790.8D695(1010) 3 NANANANANANANANA 12 16 3 3 M9Qualioy.1355556
                             5
                                                                      Rat-665711493129945
                                                                      ing:
                                                                      3
21 Sh8h4dd:169.5B82.4B203.7M2N AO NAUCH:Alel2 5 NANANANANANANANA 11 18 5 5 M2QualiNyA
                             PTS
                                                                      Rat-79501343325578
                                                                      ing:
                                                                      5
```

### **Calculate Effect Sizes**

```
df =
metafor::escalc(
    xi = ptsd_n,
    ni = participants,
    data = df,
    measure = "PLO",
    var.names = c("prev_plo", "prev_plo_var")
    )

df =
metafor::escalc(
    xi = ptsd_n,
```

```
ni = participants,
data = df,
measure = "PR",
var.names = c("prev_pr", "prev_pr_var")
)
```

### R1) Overall Prevalance (No moderations)

```
results_glmm = rma.glmm(
    xi = `ptsd_n`,
    ni = `participants`,
    data = df,
    measure="PLO",
    verbose = FALSE,
    method = "ML",
    # intercept = FALSE,
    # mods = ~ 0 + gender_male + gender_female,
    to = "all",
    test = "t" # This is recommended here metafor/html/misc-recs.html
)
summary(results_glmm)
```

```
Random-Effects Model (k = 21; tau^2 estimator: ML)
  logLik deviance
                         AIC
                                   BIC
                                            AICc
-62.9218
            0.7512 129.8436 131.9326 130.5102
tau^2 (estimated amount of total heterogeneity): 1.6743
tau (square root of estimated tau^2 value):
                                                 1.2939
I^2 (total heterogeneity / total variability):
                                                99.44%
H^2 (total variability / sampling variability): 178.00
Tests for Heterogeneity:
Wld(df = 20) = 1919.8617, p-val < .0001
LRT(df = 20) = 2737.3702, p-val < .0001
Model Results:
```

```
estimate se tval df pval ci.lb ci.ub -0.8778 0.2853 -3.0764 20 0.0060 -1.4730 -0.2826 **

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

### Prediction intervals on logit scale

These results are not helpful as they're on the logit scale, so we need to transform using the logit function below!

```
predict(results_glmm,
    level = .95
)
```

```
pred se ci.lb ci.ub pi.lb pi.ub -0.8778 0.2853 -1.4730 -0.2826 -3.6418 1.8862
```

### Prediction intervals on percentage scale

These results show that the AVERAGE prevalence is 26% 95%CI [.17, 37]

However the prediction intervals are very wide 95% CI [.02, .84].

```
pred ci.lb ci.ub pi.lb pi.ub
0.2936 0.1865 0.4298 0.0255 0.8683
```

### **Forest Plot**

### R2) Within-Study Comparison of Men and Women

### **Prepare Dataset**

```
# df_gender = df %>%
  metafor::escalc(
#
     data = .,
     ai = `male_ptsd`,
    n1i = `male_n`,
     ci = `female_ptsd`,
     n2i = `female_n`,
     measure = "PLO"
# )
df_gender = df %>%
 filter(!is.na(mptsd) & !is.na(fptsd)) %>%
 mutate(
   male_n = male,
   male_ptsd = round(male*mptsd),
   female_n = female,
   female_ptsd = round(female*fptsd)
  ) %>%
  select(authors, male_n, male_ptsd, female_n, female_ptsd)
df_gender = df_gender %>%
 metafor::escalc(
   data = .,
   ai = `male_ptsd`,
   n1i = `male_n`,
   ci = `female_ptsd`,
   n2i = `female_n`,
   measure = "OR",
   var.names = c("log.odds", "log.odds.se")
 )
df_gender %>%
   knitr::kable()
```

authors	male_n	male_ptsd	female_n	female_ptsd	log.odds	$\log.odds.se$
Abu-Kaf	65	53	108	83	0.2854205	0.1542495
Al-Hadethe	248	144	155	101	-0.3007141	0.0449793
Freh	120	77	104	50	0.6595663	0.0747613
Okello	284	57	267	50	0.0859756	0.0465574
Yilmaz	43	2	76	6	-0.5636891	0.7053426

### Meta-Analysis

```
results_glmm = rma.glmm(
  ai = `male_ptsd`,
  n1i = male_n,
  ci = `female_ptsd`,
  n2i = `female_n`,
  data = df_gender,
  measure="OR",
  model = "CM.EL",
  verbose = FALSE,
  # method = "ML",
  # intercept = FALSE,
  # mods = ~ 0 + gender_male + gender_female,
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
  # nAGQ = 1
summary(results_glmm)
```

```
Random-Effects Model (k = 5; tau^2 estimator: ML)
Model Type: Conditional Model with Exact Likelihood
  logLik deviance
                        AIC
                                  BIC
                                           AICc
-13.8148
           7.3367
                    31.6297
                              30.8485
                                        37.6297
tau^2 (estimated amount of total heterogeneity): 0.0639 (SE = 0.0887)
tau (square root of estimated tau^2 value):
                                                0.2529
I^2 (total heterogeneity / total variability):
                                                43.26%
H^2 (total variability / sampling variability): 1.76
Tests for Heterogeneity:
Wld(df = 4) = 8.5114, p-val = 0.0745
LRT(df = 4) = 8.6796, p-val = 0.0696
Model Results:
estimate
                   tval df
                               pval
                                     ci.lb
                                               ci.ub
             se
```

```
0.1042 0.1778 0.5862 4 0.5892 -0.3893 0.5977
---
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
predict(results_glmm, transf=exp, digits=3)

pred ci.lb ci.ub pi.lb pi.ub
1.110 0.678 1.818 0.470 2.618
```

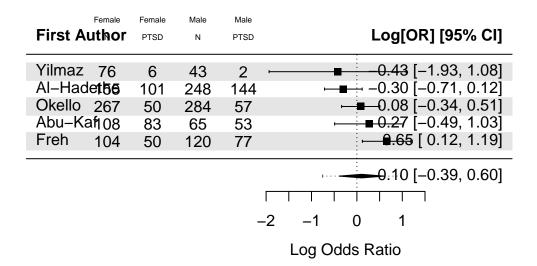
### Forest Plot

```
pdf(file.path("plots", "gender_forest.pdf"), width = 10, height = 5) # Adjust the size as ne
res = results_glmm
# forestplot =
forest(
 results_glmm,
 # transf = transf.ilogit,
 slab = authors,
 addpred = TRUE,
 steps = 10,
 order = "obs",
 ilab = cbind(female_n, female_ptsd, male_n, male_ptsd),
 header="First Author",
 ilab.xpos=(-9:-6)+3.5,
 mlab="",
 shade = TRUE
text((-9:-6)+3.5, results_glmm$k+3, c("Female", "Female", "Male", "Male"))
text((-9:-6)+3.5,
                    results_glmm$k+2, c("N", "PTSD"))
text(-5.6, -0, pos=1, cex=1, bquote(paste(
 "RE Model (K = ", .(fmtx(res$k, digits=0)),
 ", df = ", .(res$k - res$p), ", ",
  .(fmtp(res$QEp, digits=3, pname="p", add0=TRUE, sep=TRUE, equal=TRUE)), "",
  I^2, " = ", .(fmtx(res$I2, digits=1)), "%)")))
dev.off()
```

```
pdf
2
```

```
forest(
  results_glmm,
  # transf = transf.ilogit,
  slab = authors,
  addpred = TRUE,
  steps = 10,
  order = "obs",
  ilab = cbind(female_n, female_ptsd, male_n, male_ptsd),
  header="First Author",
  ilab.xpos=(-9:-6)+3.5,
  mlab="",
  shade = TRUE
)

text((-9:-6)+3.5, cex = .5,results_glmm$k+3, c("Female", "Female", "Male", "Male"))
text((-9:-6)+3.5, cex = .5, results_glmm$k+2, c("N", "PTSD"))
```



The above effect is negative, which here indicates that PTSD rates are slightly here in women across the studies, but the effect is not significant.

# R3) Meta-Regressions - age, ongoing war, method of measurement, country income level (IN PROGRESS)

```
#| echo: true
#| output: false
#| warning: false
#|
moderation_models = list()
moderation_models[["Age"]] = rma.glmm(
  xi = `ptsd_n`,
 ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
 method = "ML",
  # intercept = FALSE,
  mods = ~ 1 + age_centered,
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
)
moderation_models[["War"]] = rma.glmm(
  xi = `ptsd_n`,
 ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
  method = "ML",
  # intercept = FALSE,
  mods = ~1 + war,
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
moderation_models[["Aftermath"]] = rma.glmm(
  xi = `ptsd_n`,
  ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
 method = "ML",
```

```
# intercept = FALSE,
mods = ~ 1 + aftermath_centered,
to = "all",
test = "t" # This is recommended here metafor/html/misc-recs.html
)
```

Warning: 9 studies with NAs omitted from model fitting.

Warning: Some yi/vi values are NA.

```
moderation_models[["Measure"]] = rma.glmm(
  xi = `ptsd_n`,
  ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
  method = "ML",
  # intercept = FALSE,
 mods = ~ 1 + measure,
 to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
)
moderation_models[["Economic"]] = rma.glmm(
 xi = `ptsd_n`,
 ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
 method = "ML",
  # intercept = FALSE,
  mods = ~ 1 + factor(econindex),
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
moderation_models[["Quality"]] = rma.glmm(
  xi = ptsd_n,
  ni = `participants`,
  data = df,
  measure="PLO",
```

```
verbose = FALSE,
  method = "ML",
  # intercept = FALSE,
  mods = ~ 1 + qualityassessment_factor,
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
moderation_models_nointercept = list()
moderation_models_nointercept[["Age"]] = rma.glmm(
  xi = `ptsd_n`,
 ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
  method = "ML",
  # intercept = FALSE,
  mods = ~ 1 + age_centered,
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
)
moderation_models_nointercept[["War"]] = rma.glmm(
 xi = `ptsd_n`,
 ni = `participants`,
  data = df,
  measure="PLO",
 verbose = FALSE,
  method = "ML",
  # intercept = FALSE,
 mods = ~0 + factor(war),
  to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
moderation_models_nointercept[["Aftermath"]] = rma.glmm(
  xi = `ptsd_n`,
 ni = `participants`,
  data = df,
  measure="PLO",
  verbose = FALSE,
```

```
method = "ML",
# intercept = FALSE,
mods = ~ 1 + aftermath_centered,
to = "all",
test = "t" # This is recommended here metafor/html/misc-recs.html
)
```

Warning: 9 studies with NAs omitted from model fitting.

Warning: Some yi/vi values are NA.

```
moderation_models_nointercept[["Measure"]] = rma.glmm(
 xi = `ptsd_n`,
 ni = `participants`,
 data = df,
 measure="PLO",
 verbose = FALSE,
 method = "ML",
 # intercept = FALSE,
 mods = ~0 + measure,
 to = "all",
  test = "t" # This is recommended here metafor/html/misc-recs.html
moderation models nointercept[["Economic"]] = rma.glmm(
 xi = ptsd_n,
 ni = `participants`,
 data = df,
 measure="PLO",
 verbose = FALSE,
 method = "ML",
 # intercept = FALSE,
 mods = ~ 0 + factor(econindex),
 to = "all",
 test = "t" # This is recommended here metafor/html/misc-recs.html
moderation_models_nointercept[["Quality"]] = rma.glmm(
 xi = `ptsd_n`,
 ni = `participants`,
 data = df,
 measure="PLO",
```

```
verbose = FALSE,
method = "ML",
# intercept = FALSE,
mods = ~ 0 + qualityassessment_factor,
to = "all",
test = "t" # This is recommended here metafor/html/misc-recs.html
)
```

### Create Table

```
# moderation_models[[2]]
moderation_results = list()
for (i in 1:length(moderation_models)){
  moderation_results[[i]] = list()
  moderation_results[[i]][["QM"]]
                                  = moderation_models[[i]]$QM
  moderation_results[[i]][["QMdf_1"]] = moderation_models[[i]]$QMdf[1]
  moderation_results[[i]][["QMdf_2"]] = moderation_models[[i]]$QMdf[2]
  moderation_results[[i]][["QMp"]] = moderation_models[[i]]$QMp
 moderation_results[[i]][["N Studies"]] = length(moderation_models[[i]]$ni)
  moderation_results[[i]][["N Participants"]] = sum(moderation_models[[i]]$ni)
moderation_df <- do.call(rbind, lapply(moderation_results, function(x) as.data.frame(t(unlis-</pre>
rownames(moderation_df) = names(moderation_models)
moderation_df %>%
  gt(rowname_col = "Moderation Test",
     rownames_to_stub = TRUE) %>%
  gt::tab_header(title = "Moderation Tests") %>%
  fmt_number(columns = c(QM,QMp), decimals = 3)
```

### Moderation Tests

	QM	QMdf_1	QMdf_2	QMp	N Studies	N Participants
Age	2.654	1	19	0.120	21	12914
War	0.100	1	19	0.755	21	12914

Aftermath	8.749	1	10	0.014	12	7532
Measure	6.499	11	9	0.005	21	12914
Economic	0.173	3	17	0.913	21	12914
Quality	1.695	6	14	0.195	21	12914

```
moderation_coef = list()
for (i in 1:length(moderation_models_nointercept)){
  moderation_coef[[i]]
  moderation_coef[[i]][["QM"]] = moderation_models_nointercept[[i]]
  moderation_coef[[i]] = data.frame(
    model = names(moderation_models_nointercept)[i],
    group = rownames(moderation_models_nointercept[[i]]$beta),
          = moderation_models_nointercept[[i]][c("b")],
    ci.lb = moderation_models_nointercept[[i]][c("ci.lb")],
    ci.ub = moderation_models_nointercept[[i]][c("ci.ub")],
          = moderation_models_nointercept[[i]][c("se")],
          = moderation_models_nointercept[[i]][c("pval")]
   # moderation_coef[[i]] = moderation_coef[[i]] %>%
   # mutate(across(c(b, ci.lb, ci.ub), ~plogis(.x)))
}
moderation_coef[[match("War", names(moderation_models))]]$group = c("Ongoing War", "Aftermath
moderation_coef %>%
  do.call("bind_rows",.) %>%
  `rownames<-`((NULL)) %>%
  select(-pval) %>%
  select(-se) %>%
  mutate(group = gsub("measure","", group)) %>%
  mutate(group = gsub("factor\\(econindex\\)","", group)) %>%
  mutate(group = gsub("qualityassessment_factor","", group)) %>%
  mutate(group = gsub("intrcpt","Intercept", group)) %>%
  gt() %>%
  cols_hide("model") %>%
  tab_row_group(
    label = "Ongoing / Aftermath War, F(df1 = 1, df2 = 19) = .43, p = .84",
   rows = which(model=="War")
```