Mental Health Analysis

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Looking at Mental Health, Loneliness and Trust

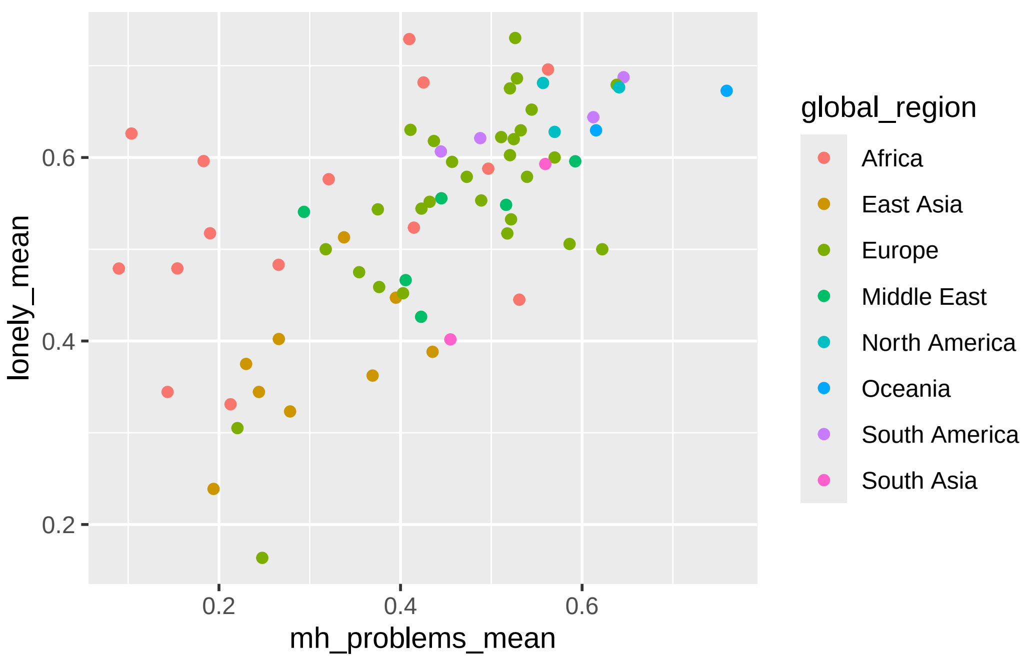
```
Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union

Warning: package 'foreign' was built under R version 4.3.3

Warning: package 'ggplot2' was built under R version 4.3.3

Warning: package 'ggrepel' was built under R version 4.3.3

Warning: package 'haven' was built under R version 4.3.2

Warning: package 'locfit' was built under R version 4.3.3

locfit 1.5-9.10      2024-06-24
```

Aggregating to the country level there is a positive relationship between loneliness and MH problems in all countries (first graph) and there appears to be a strong positive relationship between the level of MH problems and levels of loneliness across countries. But there very large differences between countries. Vietnam has ~20% of young people having MH problems and loneliness, US, Ireland, Iraq and Chile have >60%.

```
`summarise()` has grouped output by 'lonely'. You can override using the
`.groups` argument.
```

```
# A tibble: 4 x 4
  lonely mh_problems     n   prop
  <lgl>  <lgl>       <int>  <dbl>
1 FALSE  FALSE        3818 0.361
2 FALSE  TRUE         1046 0.0989
3 TRUE   FALSE        2492 0.236
4 TRUE   TRUE         3223 0.305
```

```
`summarise()` has grouped output by 'country'. You can override using the
`.groups` argument.
```

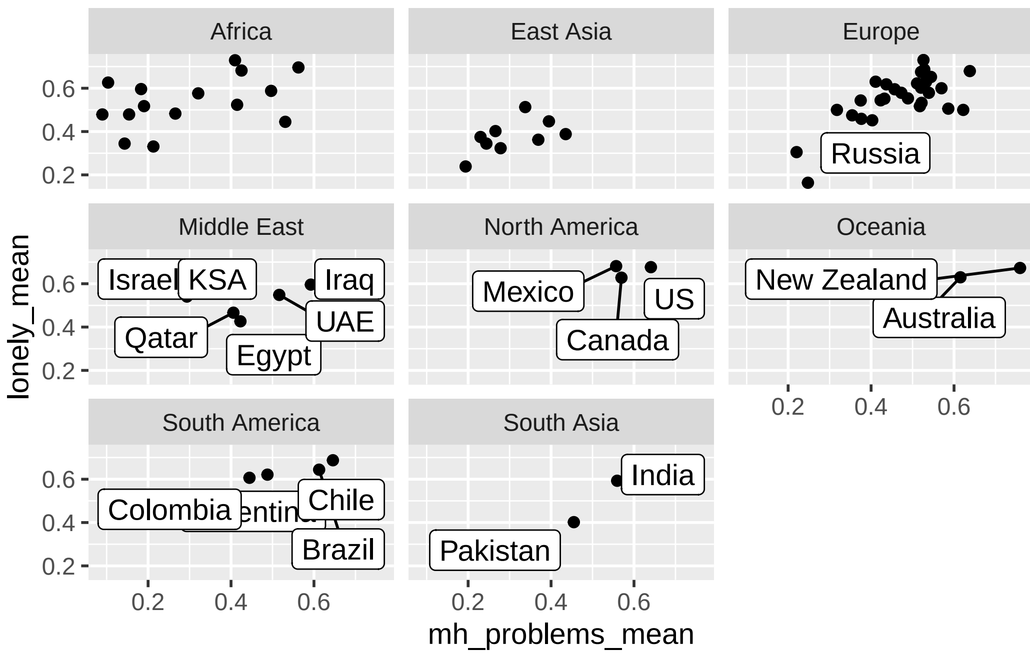



```
`summarise()` has grouped output by 'country'. You can override using the
`.groups` argument.
```

```
Warning: ggrepel: 15 unlabeled data points (too many overlaps). Consider
increasing max.overlaps
```

```
Warning: ggrepel: 9 unlabeled data points (too many overlaps). Consider
increasing max.overlaps
```

```
Warning: ggrepel: 28 unlabeled data points (too many overlaps). Consider
increasing max.overlaps
```



Are effects within countries as strong as effects between countries?

Logistic regression tells us the strength of the relationship between two variables.

The first regression shows that the parameter estimate for the relationship between loneliness and mh is 1.55 (or = 4.72). Adjusting for country, the relationship increases to 1.61 (OR 5.02) - the relationship is stronger within country than between countries.

```
Call:
glm(formula = lonely ~ mh_problems, family = "binomial", data = d_young)

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.42664    0.02575  -16.57   <2e-16 ***
mh_problemsTRUE  1.55198    0.04393   35.33   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 14597  on 10578  degrees of freedom
Residual deviance: 13221  on 10577  degrees of freedom
  (744 observations deleted due to missingness)
AIC: 13225

Number of Fisher Scoring iterations: 4

[1] 4.72081


Call:
glm(formula = lonely ~ mh_problems + country, family = "binomial",
    data = d_young)

Coefficients:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.235707   0.177849  -1.325 0.185065
mh_problemsTRUE     1.613178   0.047508  33.956  < 2e-16 ***
countryAustralia   -0.098008   0.285781  -0.343 0.731636
countryAustria     -0.283863   0.299617  -0.947 0.343425
countryBelgium      0.062253   0.301366   0.207 0.836347
countryBrazil      -0.114903   0.267201  -0.430 0.667179
countryBulgaria     0.164446   0.317859   0.517 0.604907
countryCameroon     0.047546   0.210273   0.226 0.821113
countryCanada       0.006536   0.307380   0.021 0.983035
countryChile        0.179615   0.278099   0.646 0.518366
countryColombia     0.105963   0.244027   0.434 0.664122
countryCroatia     -0.092485   0.305236  -0.303 0.761894
countryDenmark      0.049879   0.288015   0.173 0.862509
countryDRC          0.376566   0.209867   1.794 0.072763 .
countryEgypt       -0.771961   0.236432  -3.265 0.001094 **
countryEstonia     -0.519810   0.294160  -1.767 0.077212 .
countryEthiopia    -0.884056   0.209865  -4.213 2.53e-05 ***
countryFinland     -0.226757   0.298247  -0.760 0.447076
countryFrance      -0.235565   0.294300  -0.800 0.423466
countryGermany     -0.022410   0.316203  -0.071 0.943499
countryGhana       -0.222343   0.210556  -1.056 0.290977
countryGreece       0.082321   0.296089   0.278 0.780992
countryHong Kong   -0.621207   0.289639  -2.145 0.031972 *
countryHungary     -0.602654   0.297683  -2.024 0.042921 *
countryIndia       -0.255601   0.229753  -1.113 0.265922
countryIndonesia   -0.637123   0.248435  -2.565 0.010331 *
```

countryIraq	-0.283347	0.218922	-1.294	0.195566	
countryIreland	0.097276	0.291203	0.334	0.738343	
countryIsrael	-0.070893	0.260354	-0.272	0.785397	
countryItaly	0.186150	0.321035	0.580	0.562021	
countryIvory Coast	0.064184	0.222708	0.288	0.773195	
countryJapan	-1.001628	0.332764	-3.010	0.002612	**
countryKenya	-0.314644	0.208596	-1.508	0.131455	
countryKSA	-0.181468	0.234870	-0.773	0.439740	
countryLatvia	-0.485531	0.317833	-1.528	0.126605	
countryLiberia	0.100283	0.207331	0.484	0.628610	
countryLithuania	-0.307288	0.305646	-1.005	0.314718	
countryMalaysia	-0.272316	0.249953	-1.089	0.275948	
countryMali	-0.059291	0.227718	-0.260	0.794580	
countryMexico	0.269014	0.257586	1.044	0.296316	
countryNetherlands	-0.105215	0.290076	-0.363	0.716818	
countryNew Zealand	-0.160825	0.285796	-0.563	0.573620	
countryNiger	-0.155888	0.252487	-0.617	0.536965	
countryNigeria	-0.658788	0.222320	-2.963	0.003044	**
countryNorway	0.251758	0.289645	0.869	0.384739	
countryPakistan	-0.986322	0.229464	-4.298	1.72e-05	***
countryPhilippines	-0.848972	0.235126	-3.611	0.000305	***
countryPoland	-0.040595	0.308981	-0.131	0.895473	
countryPortugal	-0.506551	0.288959	-1.753	0.079598	.
countryQatar	-0.596665	0.233552	-2.555	0.010627	*
countryRomania	-0.318282	0.296044	-1.075	0.282321	
countryRussia	-1.897929	0.323718	-5.863	4.55e-09	***
countrySenegal	0.611007	0.227056	2.691	0.007124	**
countrySierra Leone	0.424681	0.210801	2.015	0.043946	*
countrySlovakia	0.085982	0.299632	0.287	0.774143	
countrySlovenia	-0.206389	0.319547	-0.646	0.518357	
countrySouth Africa	-0.961124	0.262684	-3.659	0.000253	***
countrySouth Korea	-0.946973	0.302515	-3.130	0.001746	**
countrySouth Sudan	0.716174	0.232820	3.076	0.002097	**
countrySpain	-0.222896	0.304219	-0.733	0.463753	
countrySweden	-0.795094	0.295875	-2.687	0.007204	**
countrySwitzerland	-0.342319	0.289249	-1.183	0.236620	
countryTaiwan	-0.985551	0.293602	-3.357	0.000789	***
countryThailand	-0.652674	0.293584	-2.223	0.026207	*
countryTurkey	0.490487	0.263414	1.862	0.062598	.
countryUAE	-0.381482	0.241247	-1.581	0.113811	
countryUganda	0.293504	0.226400	1.296	0.194839	
countryUK	-0.818648	0.291655	-2.807	0.005002	**
countryUkraine	-1.006358	0.347996	-2.892	0.003830	**

```
countryUS            0.047695   0.292620   0.163 0.870524    
countryVietnam      -1.328818   0.277272  -4.792 1.65e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 14597  on 10578  degrees of freedom
Residual deviance: 12720  on 10508  degrees of freedom
  (744 observations deleted due to missingness)
AIC: 12862

Number of Fisher Scoring iterations: 4
```

```
[1] 5.018736
```

Does the strength of relationship differ across countries?

The analysis below shows that it does.

The first analysis treats country as a random effect, with random intercepts. The intercepts have a variance - we know this. But the second analysis shows that allowing the relationship between mental health and loneliness to vary across countries improves the model fit (by AIC and ANOVA) suggesting that the relationship between loneliness and MH varies in strength across countries.

```
fit_3 <- lme4::glmer(
  lonely ~ mh_problems + (1 | country), data = d_young, family = "binomial"
)
summary(fit_3)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: lonely ~ mh_problems + (1 | country)
   Data: d_young

     AIC      BIC   logLik deviance df.resid 
 12920.8  12942.6  -6457.4  12914.8    10576 

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
```

```
-2.7015 -0.8083  0.4455  0.7660  2.3448

Random effects:
 Groups  Name        Variance Std.Dev.
 country (Intercept) 0.1849   0.43
Number of obs: 10579, groups:  country, 70

Fixed effects:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.49429    0.05956  -8.298   <2e-16 ***
mh_problemsTRUE  1.61252    0.04705  34.271   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr)
mh_prblTRUE -0.298
```

```
AIC(fit_3)
```

```
[1] 12920.76
```

```
fit_4 <- lme4::glmer(
  lonely ~ mh_problems + (mh_problems | country), data = d_young, family = "binomial"
)
summary(fit_4)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: lonely ~ mh_problems + (mh_problems | country)
   Data: d_young

     AIC      BIC   logLik deviance df.resid
 12877.1  12913.5  -6433.6  12867.1    10574

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.5070 -0.8313  0.4571  0.7706  2.5439
```

```
Random effects:
 Groups  Name            Variance Std.Dev. Corr
 country (Intercept)     0.2475   0.4975
         mh_problemsTRUE 0.2013   0.4487   -0.58
Number of obs: 10579, groups:  country, 70

Fixed effects:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     -0.56227    0.06801  -8.268   <2e-16 ***
mh_problemsTRUE  1.74582    0.07586  23.015   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr)
mh_prblTRUE -0.572
```

```
AIC(fit_4)
```

```
[1] 12877.12
```

```
anova(fit_3, fit_4)
```

```
Data: d_young
Models:
fit_3: lonely ~ mh_problems + (1 | country)
fit_4: lonely ~ mh_problems + (mh_problems | country)
      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
fit_3    3 12921 12943 -6457.4    12915
fit_4    5 12877 12914 -6433.6    12867 47.64  2   4.52e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Social Media Use

Using facebook daily has a much stronger association with feelings of loneliness than it does with mental health problems.

```r
d_young <-
  d_young %>% dplyr::mutate(
    facebook_daily = i18_1 == "Every day",
    facebook_daily = ifelse(i18_1 == "Don't know/ Refused", NA, facebook_daily))

d_young <- d_young %>%
  dplyr::mutate(snapchat_daily = i18_9 == "Every day",
  snapchat_daily = ifelse(i18_9 == "Don't know/ Refused", NA,
  snapchat_daily
  ))


fit_5 <- lme4::glmer(
  lonely ~ facebook_daily + (1 | country), data = d_young, family = "binomial"
)
summary(fit_5)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: lonely ~ facebook_daily + (1 | country)
   Data: d_young

     AIC      BIC   logLik deviance df.resid
  1840.1   1855.8   -917.1   1834.1     1376

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.4782 -0.7920 -0.6626  0.8947  1.5092

Random effects:
 Groups  Name        Variance Std.Dev.
 country (Intercept) 0.2879   0.5366
Number of obs: 1379, groups:  country, 11

Fixed effects:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         -0.1412     0.1802  -0.784   0.4333
facebook_dailyTRUE   0.2791     0.1162   2.402   0.0163 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Correlation of Fixed Effects:
            (Intr)
fcbk_dlTRUE -0.283
```

```r
fit_6 <- lme4::glmer(
  mh_problems ~ facebook_daily + (1 | country), data = d_young, family = "binomial"
)
summary(fit_6)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: mh_problems ~ facebook_daily + (1 | country)
   Data: d_young

     AIC      BIC   logLik deviance df.resid
  1665.3   1681.0   -829.7   1659.3     1361

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.3316 -0.7632 -0.4384  0.8662  2.4363

Random effects:
 Groups  Name        Variance Std.Dev.
 country (Intercept) 0.527    0.7259
Number of obs: 1364, groups:  country, 11

Fixed effects:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         -0.4813     0.2345  -2.053   0.0401 *
facebook_dailyTRUE   0.1318     0.1238   1.064   0.2873
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr)
fcbk_dlTRUE -0.235
```

Interaction between social media and loneliness with mental health problems

Does the relationship between social media use (facebook) and loneliness vary depending on the presence of mental health problems?

This first analysis confirms that those with MH problems are significantly more likely to experience loneliness than those without. We also find that the interaction between MH problems and daily Facebook use does not significantly affect loneliness. This suggests that daily Facebook users with MH problems do not experience significantly different levels of loneliness compared to non-daily Facebook users with MH problems.

And, are we right to assume that the association between daily facebook usage and loneliness do not vary significantly across countries? Our second analysis shows us that we are. The impact of daily facebook use on loneliness does not vary much between countries.

```r
fit_7a <- glm(
  lonely ~ mh_problems * facebook_daily,
  data = d_young,
  family = "binomial"
)
summary(fit_7a)
```

```
Call:
glm(formula = lonely ~ mh_problems * facebook_daily, family = "binomial",
    data = d_young)

Coefficients:
                                   Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -0.9067     0.1056  -8.590   <2e-16 ***
mh_problemsTRUE                      1.9433     0.1731  11.228   <2e-16 ***
facebook_dailyTRUE                   0.2895     0.1516   1.909   0.0562 .
mh_problemsTRUE:facebook_dailyTRUE  -0.2219     0.2522  -0.880   0.3789
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1841.0  on 1328  degrees of freedom
Residual deviance: 1597.5  on 1325  degrees of freedom
  (9994 observations deleted due to missingness)
AIC: 1605.5
```

```
Number of Fisher Scoring iterations: 4
```

```r
fit_7a_mh <- glm(
  mh_problems ~ lonely * facebook_daily,
  data = d_young,
  family = "binomial"
)
summary(fit_7a_mh)
```

```

Call:
glm(formula = mh_problems ~ lonely * facebook_daily, family = "binomial",
    data = d_young)

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                   -1.46634    0.13074 -11.215   <2e-16 ***
lonelyTRUE                     1.94326    0.17308  11.228   <2e-16 ***
facebook_dailyTRUE             0.09241    0.19400   0.476    0.634
lonelyTRUE:facebook_dailyTRUE -0.22194    0.25224  -0.880    0.379
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1779.0  on 1328  degrees of freedom
Residual deviance: 1538.4  on 1325  degrees of freedom
  (9994 observations deleted due to missingness)
AIC: 1546.4

Number of Fisher Scoring iterations: 4
```

```r
fit_7b <- lme4::glmer(
  lonely ~ mh_problems * facebook_daily + (facebook_daily | country),
  data = d_young,
  family = "binomial"
)
summary(fit_7b)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
```

```
  Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: lonely ~ mh_problems * facebook_daily + (facebook_daily | country)
   Data: d_young

     AIC      BIC   logLik deviance df.resid
  1600.3   1636.7   -793.2   1586.3     1322

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.0280 -0.7003 -0.5329  0.6513  1.8764

Random effects:
 Groups  Name               Variance  Std.Dev. Corr
 country (Intercept)        0.1051766 0.32431
         facebook_dailyTRUE 0.0005632 0.02373  1.00
Number of obs: 1329, groups:  country, 11

Fixed effects:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                        -0.8546     0.1479  -5.778 7.58e-09 ***
mh_problemsTRUE                     1.8295     0.1797  10.179  < 2e-16 ***
facebook_dailyTRUE                  0.3385     0.1593   2.125   0.0336 *
mh_problemsTRUE:facebook_dailyTRUE -0.2593     0.2595  -0.999   0.3177
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) mh_TRUE f_TRUE
mh_prblTRUE -0.462
fcbk_dlTRUE -0.461  0.405
m_TRUE:_TRU  0.306 -0.669  -0.608
```

```r
fit_7b_mh <- lme4::glmer(
  mh_problems ~ lonely * facebook_daily + (facebook_daily | country),
  data = d_young,
  family = "binomial"
)
```

```
boundary (singular) fit: see help('isSingular')
```

```r
summary(fit_7b_mh)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: mh_problems ~ lonely * facebook_daily + (facebook_daily | country)
   Data: d_young

     AIC      BIC   logLik deviance df.resid
  1451.8   1488.1   -718.9   1437.8     1322

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.7823 -0.6186 -0.2867  0.6248  3.5241

Random effects:
 Groups  Name               Variance Std.Dev. Corr
 country (Intercept)        0.343043 0.58570
         facebook_dailyTRUE 0.009532 0.09763  1.00
Number of obs: 1329, groups:  country, 11

Fixed effects:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                    -1.3969     0.2237  -6.243 4.29e-10 ***
lonelyTRUE                      1.8085     0.1810   9.991  < 2e-16 ***
facebook_dailyTRUE              0.2075     0.2094   0.991    0.322
lonelyTRUE:facebook_dailyTRUE  -0.2731     0.2659  -1.027    0.304
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) lnTRUE f_TRUE
lonelyTRUE  -0.455
fcbk_dlTRUE -0.287  0.488
lTRUE:_TRUE  0.310 -0.677 -0.748
optimizer (Nelder_Mead) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')
```

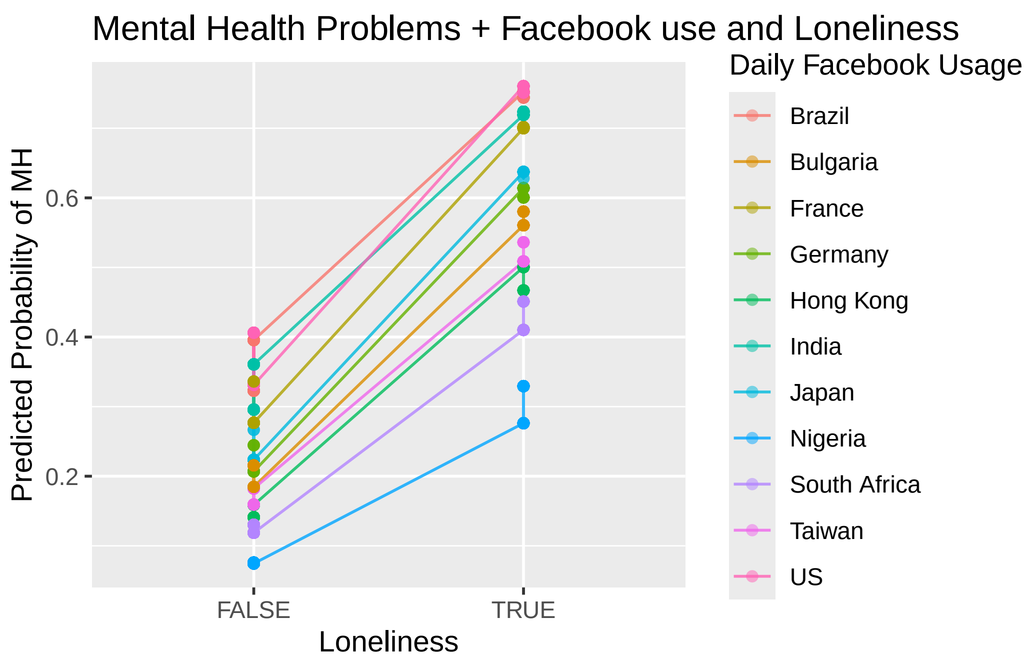
```r
AIC(fit_7a, fit_7b)
```

```
       df      AIC
```

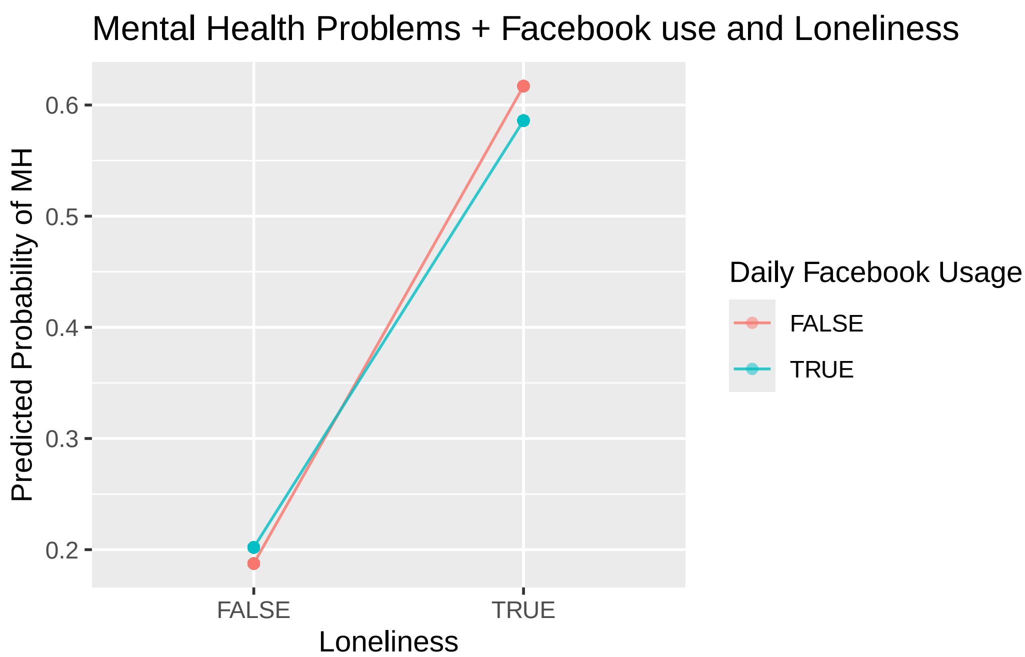
```
fit_7a   4 1605.454
fit_7b   7 1600.338
```

Visualizing Loneliness, Mental Health Problems, and their Interaction across countries

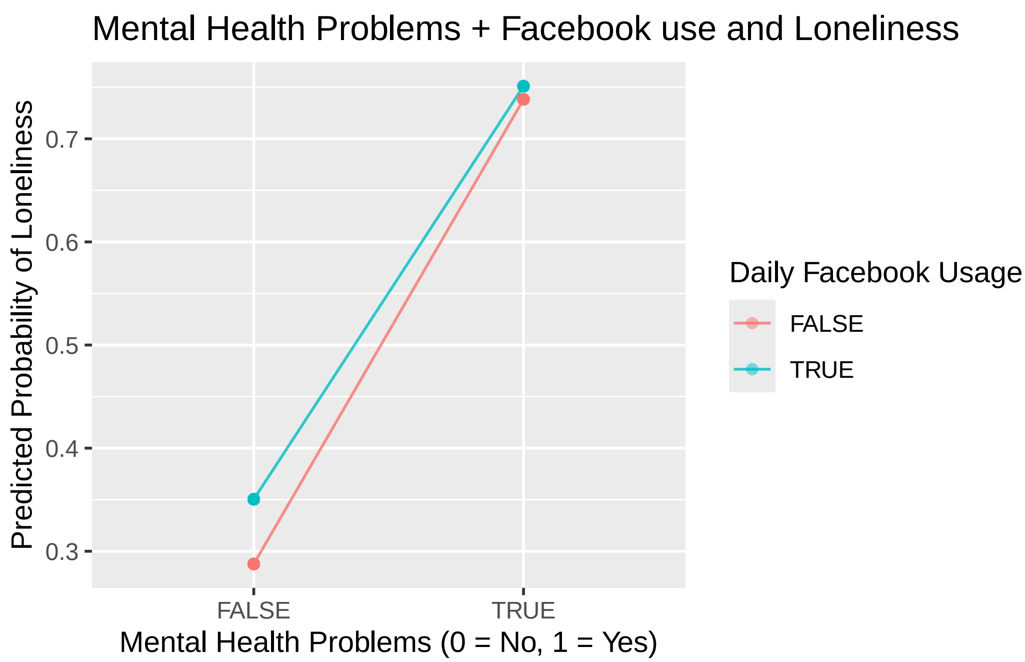
```r
d_young_clean <- d_young %>%
  dplyr::filter(!is.na(mh_problems) & !is.na(facebook_daily) & !is.na(lonely))

predicted_lonely_a <- predict(fit_7a, type = "response")
predicted_lonely_b <- predict(fit_7b, type = "response")

predicted_mh_a <- predict(fit_7a_mh, type = "response")
predicted_mh_b <- predict(fit_7b_mh, type = "response")



ggplot(d_young_clean, aes(x = lonely,
                          y = predicted_mh_b,
                          color = country, group = country)) +
  geom_line(alpha = 0.8) +
  geom_point(alpha = 0.5) +
  labs(
    title = "Mental Health Problems + Facebook use and Loneliness",
    x = "Loneliness",
    y = "Predicted Probability of MH",
    color = "Daily Facebook Usage"
  )
```



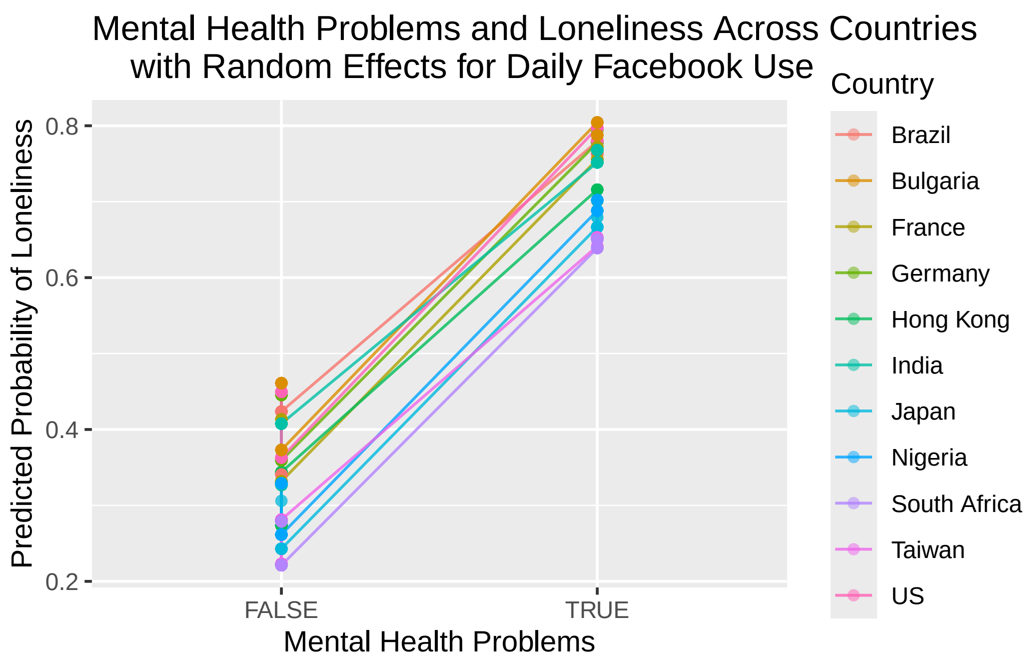

```r
ggplot(d_young_clean, aes(x = lonely,
                          y = predicted_mh_a,
                          color = facebook_daily, group = facebook_daily)) +
  geom_line(alpha = 0.8) +
  geom_point(alpha = 0.5) +
  labs(
    title = "Mental Health Problems + Facebook use and Loneliness",
    x = "Loneliness",
    y = "Predicted Probability of MH",
    color = "Daily Facebook Usage"
  )
```




```
ggplot(d_young_clean, aes(x = mh_problems,
                          y = predicted_lonely_a,
                          color = facebook_daily, group = facebook_daily)) +
  geom_line(alpha = 0.8) +
  geom_point(alpha = 0.5) +
  labs(
    title = "Mental Health Problems + Facebook use and Loneliness",
    x = "Mental Health Problems (0 = No, 1 = Yes)",
    y = "Predicted Probability of Loneliness",
    color = "Daily Facebook Usage"
  )
```




```r
ggplot(d_young_clean, aes(x = mh_problems,
                          y = predicted_lonely_b,
                          color = country, group = country)) +
  geom_line(alpha = 0.8) +
  geom_point(alpha = 0.5) +
  labs(
    title = "Mental Health Problems and Loneliness Across Countries
    with Random Effects for Daily Facebook Use",
    x = "Mental Health Problems",
    y = "Predicted Probability of Loneliness",
    color = "Country"
  )
```



The first graph allows us to visualize the strong correlation between mental health problems and loneliness, as indicated by the steep slope. We also visualize that daily facebook usage on its own is not a very good predictor of loneliness, as those reporting daily facebook usage only have a marginally higher predicted probability of loneliness. Finally, this graph allows us to visualize a lack of interaction effect between MH problems and loneliness. Because the lines are relatively parallel, it shows that the relationship between facebook use and loneliness does not vary depending on the presence of MH problems.

The second graph gives us more visualization for within countries. While hard to see, there are 22 points for each MH outcome. The 11 countries for facebook usage being false, and the same 11 for when it is true. Because the lines are relatively parallel, this graph shows us that even within countries, daily facebook use does not cause an interaction effect on MH problems and loneliness.

```
ggplot(d_young_clean, aes(x = facebook_daily,
                          y = predicted_mh_a,
                          color = facebook_daily, group = facebook_daily)) +
  geom_line(alpha = 0.8) +
  geom_point(alpha = 0.5) +
  labs(
    title = "Mental Health Problems + Facebook use and Loneliness",
    x = "Loneliness",
```

```
    y = "Predicted Probability of MH",
    color = "Daily Facebook Usage"
  )
```