

## HW 9

Chelsey Pan + Mengzhao Yan

2022-11-13

### Research Background

Given that the population is aging, an increasing number of people in the society are expected to experience physical strains. The mind and body connection concept tells us that mental health and physical health are related. A sizeable number of studies have demonstrated the association of chronic conditions with mental distress and identified physical health constraint as a critical risk to mental well-being in later life. Building upon this connection, many studies have identified some the factors protecting older adults from the negative mental health outcomes due to functional difficulties. Social support is among the protective factors. However, less is known about the mechanism of how social support might buffer functional difficulties related negative mental health impact among diverse racial/ethnic groups. Considering that different racial/ethnic groups are heterogeneous between each other and variabilities exist within each racial/ethnic group, whether the social support could protect older adults from negative mental health related to functional difficulties in a consistent way is worthy more investigation, which would inform how to design interventions to use social support more effectively to help older adults from diverse racial/ethnic groups to cope negative mental health impact related to functional difficulties.

### Research Questions

Using three rounds of data from the National Social Life, Health, and Aging Project (NSHAP), we hope to investigate (1) whether functional difficulties (difficulties in activities of daily living) would contribute to negative mental health outcome (depressive symptoms in our data); (2) whether social support would contribute to positive mental health outcome; (3) whether social support would modify the relationship between functional difficulties and mental health outcome; (4) whether the findings to the aforementioned (1) (2) (3) questions would keep consistent in older adults from diverse racial/ethnic groups.

### Structure of Data

Level 1: individuals; Level 2: repeated measurements

### Plan of Analysis

We plan to use time-varying model as our modeling strategy. We would use depressive symptoms as the dependent variable and run a set of multivariate regressions including: (1) Model 1: check the relationship between background variables and depressive symptoms; (2) Model 2: Model 1 + functional difficulties + social support; (3) Model 3: Model 2 + functional difficulties  $\times$  social support; (4) If we find a significant interaction between functional difficulties and social support in Model 3, we would either

include a three way interaction term, which is functional difficulties × social support × race/ethnicity in Model 4, or stratify the full sample into subsamples based on race/ethnicity to see if the interaction between functional difficulties and social support stay consistent in stratified subsample. If we do not find a significant interaction between functional difficulties and social support in Model 3, our analysis would end at Model 3.

## Variables

The outcome variable **depressive symptoms** in the three rounds of NSHAP data is measured by an existing 11-item short form of the Center for Epidemiologic Studies Depression Scale (CES-D).

Scale: 1 = rarely or none of the time to 4 = most of the time

Cronbach's alpha: 0.80 (round 1), 0.79 (round 2), 0.82 (round3)

Coding: Adding the score of each item together .

The variables we used are deptot1 (round 1), deptot2 (round 2), deptot3 (round 3)

The major independent variable **functional difficulties** in activities of daily living in the three rounds of NSHAP data is measured by the degree of difficulty completing the following ADL activities: (a) walking one block, (b) walking across a room, (c) dressing, including putting on shoes and socks, (d) bathing or showering, (e) eating, such as cutting up food, (f) getting in or out of bed, and (g) using the toilet, including getting up and down.

Scale: 0 = no difficulty to 3 = unable to do

Coding: After checking previous literature on how this scales has been used, we binarized the response to each question as "0 = no difficulty", "1 = have some difficulty", and then added up the value of the response to each question together so the total score can indicate how many difficulties the respondent has in terms of ADL.

Cronbach's alpha: 0.81 (round 1), 0.83 (round 2), 0.83 (round 3)

The variables we used are adltotb1 (round 1), adltotb2 (round 2), adltotb3 (round 3)

The major independent variable **social support** is measured from three dimensions including partner support, family support, and friend support. The questions include (a) How often can you open up to partner if you need to talk about your worries? (b) How often can you rely on partner for help if you have a problem? (c) How often can you open up to members of your family if you need to talk about your worries? (d) How often can you rely on family for help if you have a problem? (e) How often can you open up to your friends if you need to talk about your worries? (f) How often can you rely on friends for help if you have a problem?

Scale: 1 = hardly ever or never to 3 = often

Coding: We found previous studies have added partner support, family support, and friends support together to indicate the total amount of social support. Thus, we added the 6 questions together to indicate total social support.

Cronbach's alpha: 0.64 (round 1), 0.63 (round 2), 0.66 (round 3)

The variables we used are socsuptot1 (round 1), socsuptot2 (round 2), socsuptot3 (round 3)

Covariates:

Age: age1, age2, age3; mean age1 = 69, mean age2 = 73, mean age3 = 68 Since NSHAP recruits new research participants in each round, the mean age is not in a increasing pattern.

Gender: female1, female2, female3; 1 = Female, 0 = Male

Race/Ethnicity: race1, race2, race3; 1= non-Hispanic White, 2 = non-Hispanic, Black, 3 = Hispanic, 4 = Other

Marital Status: marital1, marital2, marital3; 1= Married, 0 = Unmarried

Education level: edulevel1, edulevel2, edulevel3; 1 = >12 years, 0 = <or=12 years

## Preliminary Analysis

In our preliminary analysis, we transformed the data from wide format into long format, explored the correlation between major variables, examined the ICC of depressive symptoms over time, and investigated the relationship between depressive symptoms and functional difficulties in regression analysis using time-varying model strategy.

```
# Load packages
library(tidyverse)
library(haven)
library(here)
library(lme4)
library(lmerTest)
library(modelsummary)
library(brms)

# Load data
df <- read_dta('psyc575finalupdated.dta')
```

Reformat data wide to long

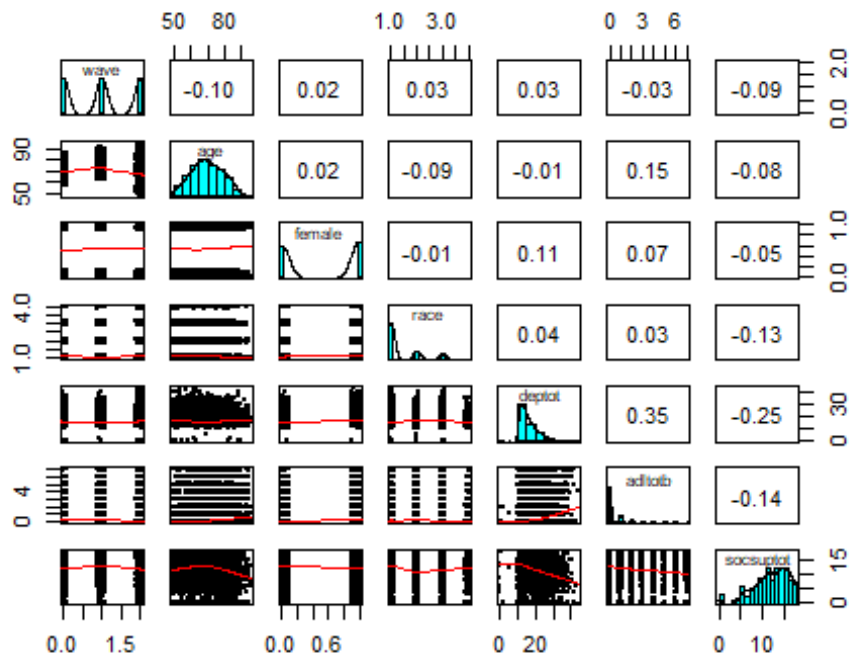
```
# Reformat from wide to long
df_long <- df %>%
  select(-c(`_merge1`, `_merge2`, round1:round3)) %>%
  pivot_longer(c(-ID),
               names_to = c('.value', 'round'),
               names_pattern = "(age|female|race|marital|edulevel|deptot|adltotb|socsuptot|weight_adj|weight_sel)([1-3])",
```

```
names_transform = list(round = as.integer)) %>%
mutate(round = round - 1) # Convert round from 1-3 to 0-2
```

Data exploration

*# Spread of predictors*

```
df_long %>%
  select(round, age, female, race, deptot, adltotb, socsuptot) %>%
  psych::pairs.panels(jiggle = TRUE, factor = 0.5, ellipses = FALSE,
    cex.cor = 1, cex = 0.5)
```



*# Analysis of attrition*

*# Add complete/incomplete variable*

```
df_comp <- df %>%
  # Compute summaries by rows
  rowwise() %>%
  # First compute the number of missing occasions
  mutate(nmis_deptot = sum(is.na(c_across(deptot1:deptot3))),
    # Complete only when nmis_read = 0
    complete = if_else(nmis_deptot == 0, "complete", "incomplete")) %>%
  %
  ungroup()
# Compare the differences
datasummary((deptot1 + socsuptot1 + adltotb1 + age1 + female1 + race1 + marit
all1 + edulevel1) ~
  complete * (Mean + SD), data = df_comp)
```

	complete / Mean	complete / SD	incomplete / Mean	incomplete / SD
deptot1	15.84	4.95	17.29	5.44
socsuptot1	12.91	3.70	11.29	4.35
adltotb1	0.61	1.31	1.27	1.87
age1	66.69	6.81	72.10	7.93
female1	0.54	0.50	0.49	0.50
race1	1.44	0.77	1.45	0.77
marital1	0.67	0.47	0.52	0.50
edulevel1	0.58	0.49	0.43	0.49

It looks like there is a noticeable difference in the mean age of participants at round 1 who didn't complete all 3 rounds. It's possible that some of the participants didn't complete all 3 rounds due to passing away, however this is hard to ascertain given that not all participants in the study began at round 1. The other prominent difference was a higher average amount of physical difficulties among the participants who didn't complete all 3 rounds.

ICC

```
# ICC for outcome - depression symptoms score
m0_dep <- lmer(deptot ~ (1 | ID), data = df_long)
performance::icc(m0_dep)

## # Intraclass Correlation Coefficient
##
##      Adjusted ICC: 0.570
##      Unadjusted ICC: 0.570

# ICC for predictor 1: physical health difficulties
m0_adl <- lmer(adltotb ~ (1 | ID), data = df_long)
performance::icc(m0_adl)

## # Intraclass Correlation Coefficient
##
##      Adjusted ICC: 0.546
##      Unadjusted ICC: 0.546

# ICC for predictor 2: social support score
m0_socsup <- lmer(socsuptot ~ (1 | ID), data = df_long)
performance::icc(m0_socsup)
```

```
## # Intraclass Correlation Coefficient
##
##     Adjusted ICC: 0.522
##     Unadjusted ICC: 0.522
```

Variability at the individual level accounts for about 57% of the total variability in total depression symptom scores. The ICC for the physical health score predictor was 0.546, while the ICC for the social support predictor was 0.522.

Bonus: ICC of outcome using brms

```
# Run unconditional model predicting depression scores
m0 <- brm(deptot ~ (1 | ID), data = df_long,
          seed = 123,
          file = 'dep_icc')

# Get summary
summary(m0)

## Family: gaussian
## Links: mu = identity; sigma = identity
## Formula: deptot ~ (1 | ID)
## Data: df_long (Number of observations: 10578)
## Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##       total post-warmup draws = 4000
##
## Group-Level Effects:
## ~ID (Number of levels: 6069)
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)    4.05      0.06    3.92    4.16 1.00      893    2031
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept    16.70      0.06    16.58    16.83 1.00     1767    2572
##
## Family Specific Parameters:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma         3.52      0.04     3.45     3.59 1.00     1152    2153
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

# Obtain ICC
performance::icc(m0)

## # Intraclass Correlation Coefficient
##
##     Adjusted ICC: 0.569
##     Unadjusted ICC: 0.569
```

```

# Get conditional ICC
m_cs <- brm(deptot ~ 0 + factor(round) + (1 | ID),
  data = df_long,
  seed = 123,
  file = 'dep_icc_cs')

# Get summary
summary(m_cs)

## Family: gaussian
## Links: mu = identity; sigma = identity
## Formula: deptot ~ 0 + factor(round) + (1 | ID)
## Data: df_long (Number of observations: 10578)
## Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
## total post-warmup draws = 4000
##
## Group-Level Effects:
## ~ID (Number of levels: 6069)
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)    4.05      0.06    3.92    4.17 1.00      859    1748
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## factorround0    16.58      0.09    16.40    16.76 1.00      2277    2545
## factorround1    16.30      0.09    16.13    16.48 1.00      2236    2477
## factorround2    17.01      0.08    16.86    17.16 1.00      2025    2913
##
## Family Specific Parameters:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma          3.50      0.04     3.43     3.58 1.00      1115    1927
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

# Obtain ICC
performance::icc(m_cs)

## # Intraclass Correlation Coefficient
##
## Adjusted ICC: 0.572
## Unadjusted ICC: 0.570

```

Using brms, you get about the same ICC.

Separate time-varying predictors into within-person and between-person levels

```

df_long <- df_long %>%
  group_by(ID) %>%
  mutate(across(c(adltotb, socsuptot),
    list("pm" = ~ mean(., na.rm = TRUE),

```

```

    "pmc" = ~ . - mean(., na.rm = TRUE)))) %>%
  mutate(race = as.factor(race))

```

## Model Equations

Lvl 1:

$$\text{deptot}_{ti} = \beta_{0i} + \beta_{1i}\text{adltotb\_pmc}_{ti} + e_{ti}$$

Lvl 2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\text{adltotb\_pm}_{i} + \gamma_{02}\text{race}_{i} + \gamma_{03}\text{adltotb\_pm}_{i} \times \text{race}_{i} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}\text{race}_{i} + u_{1i}$$

Preliminary analysis

Base model: Is there an association between reported physical difficulties and depressive symptoms across the 3 rounds, and does this interact with participant race (treated as a lvl 2 predictor in this case)

Our preliminary analysis shown that more functional difficulties is significantly associated with increased depressive symptoms within individuals and across individuals. 1 unit increase in functional difficulties is associated with 0.60 unit increase in depressive symptoms within individuals (95% CI: 0.45 to 0.73). 1 unit increase in functional difficulties is associated with 1.35 units increase in depressive symptoms across individuals (95% CI: 1.25 to 1.45). Interestingly, we found that compared to non-Hispanic Whites, the negative impact of functional disability on mental health is less pronounced in non-Hispanic Blacks at between-individual level. When experiencing the same level of functional disabilities as non-Hispanic Whites, non-Hispanic Blacks tend to have 0.28 unit less depressive symptoms (95% CI: -0.48 to -0.08).

```

# Model with just functional health difficulties
m1 <- brm(deptot ~ (adltotb_pm + adltotb_pmc) * race + (adltotb_pmc | ID),
  data = df_long,
  seed = 123,
  file = 'dep_physicalhealth_race')

# Get model summary
summary(m1)

## Family: gaussian
## Links: mu = identity; sigma = identity
## Formula: deptot ~ (adltotb_pm + adltotb_pmc) * race + (adltotb_pmc | ID)
## Data: df_long (Number of observations: 10543)
## Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
## total post-warmup draws = 4000
##
## Group-Level Effects:

```



```

## ~ID (Number of levels: 6052)
##
## Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_
ESS
## sd(Intercept)          3.67      0.06      3.56      3.79 1.01
822
## sd(adltotb_pmc)        0.93      0.08      0.77      1.09 1.00
928
## cor(Intercept,adltotb_pmc) 0.25      0.07      0.12      0.40 1.00      1
742
##
## Tail_ESS
## sd(Intercept)          1500
## sd(adltotb_pmc)        1855
## cor(Intercept,adltotb_pmc) 2206
##
## Population-Level Effects:
## Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_
ESS
## Intercept              15.38      0.08      15.22      15.54 1.00      1119      2
308
## adltotb_pm             1.35      0.05      1.25      1.45 1.01      1391      2
199
## adltotb_pmc            0.60      0.07      0.45      0.73 1.00      2641      2
915
## race3                  0.71      0.23      0.24      1.15 1.00      1284      2
300
## race2                  0.61      0.19      0.23      1.00 1.01      1394      1
959
## race4                  0.42      0.37     -0.30      1.14 1.00      1336      2
113
## adltotb_pm:race3       -0.16      0.12     -0.39      0.07 1.00      1467      2
045
## adltotb_pm:race2       -0.28      0.10     -0.48     -0.08 1.00      1396      2
277
## adltotb_pm:race4       -0.14      0.24     -0.61      0.32 1.00      1729      2
246
## adltotb_pmc:race3      -0.20      0.19     -0.56      0.16 1.00      2573      2
452
## adltotb_pmc:race2      -0.16      0.15     -0.46      0.14 1.00      2759      3
223
## adltotb_pmc:race4       0.22      0.44     -0.65      1.08 1.00      4120      3
256
##
## Family Specific Parameters:
## Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma      3.34      0.04      3.26      3.42 1.01      752      1410
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

```

Table summarizing model results

```
# Summarize the model results
msummary(list('m1' = m1),
          statistic = "[{conf.low}, {conf.high}]",
          shape = effect + term ~ model)
```

		m1
fixed	b_Intercept	15.380 [15.222, 15.543]
	b_adltotb_pm	1.351 [1.250, 1.446]
	b_adltotb_pmc	0.597 [0.453, 0.735]
	b_race3	0.708 [0.241, 1.150]
	b_race2	0.608 [0.231, 0.996]
	b_race4	0.426 [-0.296, 1.137]
	b_adltotb_pm × race3	-0.161 [-0.387, 0.070]
	b_adltotb_pm × race2	-0.278 [-0.479, -0.082]
	b_adltotb_pm × race4	-0.143 [-0.610, 0.321]
	b_adltotb_pmc × race3	-0.204 [-0.561, 0.164]
	b_adltotb_pmc × race2	-0.161 [-0.457, 0.139]

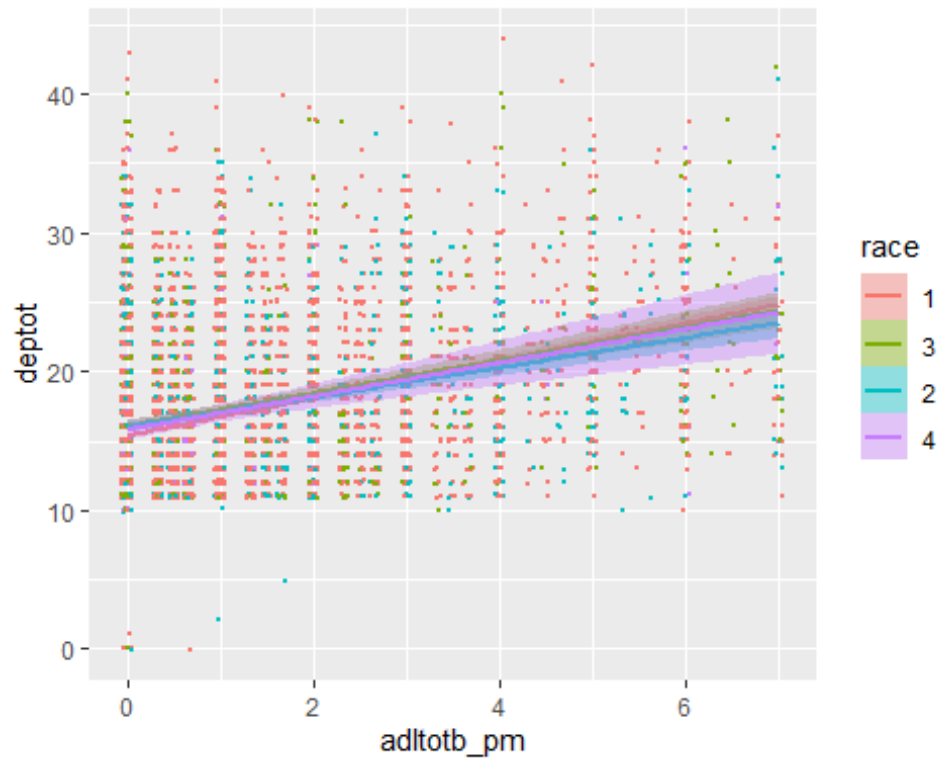
		m1
random	b_adltotb_pmc x race4	0.208 [-0.647, 1.080]
	sigma	3.339 [3.261, 3.423]
	sd_ID__Intercept	3.671 [3.556, 3.791]
	sd_ID__adltotb_pmc	0.926 [0.766, 1.092]
	cor_ID__Intercept__adltotb_pmc	0.254 [0.117, 0.396]
	Num.Obs.	10543
	R2	0.599
	R2 Adj.	0.351
	R2 Marg.	0.128
	ELPD	-30335.7
	ELPD s.e.	97.9
	LOOIC	60671.5
	LOOIC s.e.	195.7
	WAIC	59614.4
	RMSE	2.60
	r2.adjusted.marginal	0.123

Figures showing association between main predictor and outcome

```

# Figure showing association between adltotb_pm and depression symptoms,
# split by race
figures[4]
## $`adltotb_pm:race`

```



```

# Figure showing association between adltotb_pmc and depression symptoms
# split by race
figures[5]
## $`adltotb_pmc:race`

```

