Affect and SM Use - SMASH Study

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08/19/2022

Descriptive Statistics

```
## Age

wide <- data[which(data$day_in_study==1 & data$hour_in_study==1),] # create dataset with 1 row/particip


mean(wide$Age, na.rm=TRUE)
```

```
## [1] 15.84211
```

```
sd(wide$Age, na.rm=TRUE)
```

```
## [1] 1.014515
```

```
## Race

table(wide$Race_012)
```

```
##
##  0  1  2
## 15  2  2
```

```
table(wide$Gender)
```

```
##
##  0  1  2
##  7 11  1
```

```
## Days in Study

# summarize max days in study
Max_days <- data %>%
  group_by(pid) %>%
  summarise(Max_day = max(day_in_study, na.rm=TRUE))

# get mean/sd day in study
mean(Max_days$Max_day, na.rm=TRUE)
```

```
## [1] 30.57895
```

```r
sd(Max_days$Max_day, na.rm=TRUE)
```

```
## [1] 5.620555
```

```r
## Get Means/SDs of SM time spent

sm_summary <- day %>%
  group_by %>%
  summarise(sm_time = (mean(sum_sm, na.rm=TRUE) * 60), sm_checks = mean(count_sm, na.rm=TRUE))
```

Negative Mood - Bayesian Framework

```r
###check utility of random slopes
model1 <- lmer(NAf_pm_p ~ sum_sm_p + NAf_am_p + sum_sm_p_c + day_in_study + (1 | pid), data = day)
model2 <- lmer(NAf_pm_p ~ sum_sm_p + NAf_am_p + sum_sm_p_c + day_in_study + (sum_sm_p | pid), data = day

anova(model1, model2)
```

```
## Data: day
## Models:
## model1: NAf_pm_p ~ sum_sm_p + NAf_am_p + sum_sm_p_c + day_in_study + (1 | pid)
## model2: NAf_pm_p ~ sum_sm_p + NAf_am_p + sum_sm_p_c + day_in_study + (sum_sm_p | pid)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## model1    7 2466.7 2492.3 -1226.3   2452.7
## model2    9 2470.7 2503.6 -1226.3   2452.7     0  2          1
```

```r
model3 <- lmer(NAf_pm_p ~ count_sm_p + NAf_am_p + count_sm_p_c + day_in_study + (1 | pid), data = day)
model4 <- lmer(NAf_pm_p ~ count_sm_p + NAf_am_p + count_sm_p_c + day_in_study + (count_sm_p | pid), data

anova(model3, model4)
```

```
## Data: day
## Models:
## model3: NAf_pm_p ~ count_sm_p + NAf_am_p + count_sm_p_c + day_in_study + (1 | pid)
## model4: NAf_pm_p ~ count_sm_p + NAf_am_p + count_sm_p_c + day_in_study + (count_sm_p | pid)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## model3    7 2462.7 2488.3 -1224.4   2448.7
## model4    9 2466.7 2499.6 -1224.4   2448.7     0  2          1
```

```r
## Negative mood - sumduration
NA_sm_sum_bayes  <- brm(NAf_pm_p ~ sum_sm_p + NAf_am_p + sum_sm_p_c + day_in_study + (1 | pid), prior =
```

```
##
## SAMPLING FOR MODEL '48186b7868f5edea6c7fb9df0f161535' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
```

```
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 1.984 seconds (Warm-up)
## Chain 1:                0.35 seconds (Sampling)
## Chain 1:                2.334 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL '48186b7868f5edea6c7fb9df0f161535' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 1.322 seconds (Warm-up)
## Chain 2:                0.479 seconds (Sampling)
## Chain 2:                1.801 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL '48186b7868f5edea6c7fb9df0f161535' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
```

```
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 1.946 seconds (Warm-up)
## Chain 3:                0.464 seconds (Sampling)
## Chain 3:                2.41 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL '48186b7868f5edea6c7fb9df0f161535' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 1.374 seconds (Warm-up)
## Chain 4:                0.472 seconds (Sampling)
## Chain 4:                1.846 seconds (Total)
## Chain 4:
```

```
                    # family = "gaussian", data = day, warmup = 2.5e3, iter = 1.5e4, thin = 1,
                    # chains = 4, cores = 4, seed = "123",control = list(adapt_delta = 0.999, max_treede

model_parameters(NA_sm_sum_bayes, centrality = "mean")
```

```
## # Fixed effects
##
## Parameter    |     Mean |        95% CI |     pd | % in ROPE |  Rhat |     ESS
## ------------------------------------------------------------------------------
## (Intercept)  |    -2.15 | [-7.50, 3.30] | 78.77% |    39.54% | 1.000 | 5355.00
## sum_sm_p     | 9.09e-03 | [-0.02, 0.04] | 75.35% |      100% | 1.000 | 5937.00
```

```
## NAf_am_p     |     0.11 | [ 0.01, 0.22] | 98.47% |      100% | 0.999 | 5019.00
## sum_sm_p_c   | 7.69e-05 | [-0.04, 0.04] | 50.15% |      100% | 1.000 | 5336.00
## day_in_study |     0.11 | [-0.14, 0.35] | 80.53% |      100% | 1.001 | 4526.00
##
## # Fixed effects sigma
##
## Parameter |  Mean |         95% CI |   pd | % in ROPE |  Rhat |     ESS
## ------------------------------------------------------------------------
## sigma     | 18.07 | [16.63, 19.69] | 100% |        0% | 0.999 | 6099.00
```

```r
standard_error(NA_sm_sum_bayes)
```

```
##        Parameter         SE
## 1    b_Intercept 2.72814428
## 2     b_sum_sm_p 0.01332453
## 3     b_NAf_am_p 0.05233454
## 4   b_sum_sm_p_c 0.01852566
## 5 b_day_in_study 0.12438486
## 6          sigma 0.78088042
```

```r
## Negative mood - counts

NA_sm_count_bayes  <- brm(NAf_pm_p ~ count_sm_p + NAf_am_p + count_sm_p_c + day_in_study + (1 | pid), p
                    family = "gaussian", data = day, warmup = 2.5e3, iter = 1.5e4, thin = 1,
                    chains = 4, cores = 4, seed = "123",control = list(adapt_delta = 0.999, max_treedep
model_parameters(NA_sm_count_bayes, centrality = "mean")
```

```
## # Fixed effects
##
## Parameter    |      Mean |        95% CI |     pd | % in ROPE |  Rhat |      ESS
## ---------------------------------------------------------------------------------
## (Intercept)  |     -1.34 | [-6.99, 4.31] | 68.18% |    45.24% | 1.000 | 67825.00
## count_sm_p   |      0.03 | [ 0.00, 0.06] | 97.50% |      100% | 1.000 | 74712.00
## NAf_am_p     |      0.11 | [ 0.01, 0.22] | 98.40% |      100% | 1.000 | 67712.00
## count_sm_p_c | -8.18e-03 | [-0.03, 0.02] | 73.63% |      100% | 1.000 | 64640.00
## day_in_study |      0.12 | [-0.11, 0.36] | 84.72% |      100% | 1.000 | 69651.00
##
## # Fixed effects sigma
##
## Parameter |  Mean |         95% CI |   pd | % in ROPE |  Rhat |      ESS
## -------------------------------------------------------------------------
## sigma     | 17.95 | [16.54, 19.53] | 100% |        0% | 1.000 | 72278.00
```

```r
standard_error(NA_sm_count_bayes)
```

```
##        Parameter         SE
## 1    b_Intercept 2.88429980
## 2   b_count_sm_p 0.01628317
## 3     b_NAf_am_p 0.05360910
## 4 b_count_sm_p_c 0.01291515
## 5 b_day_in_study 0.12152237
## 6          sigma 0.76326959
```

Positive Affect on SM - Within-Day Models Bayesian

```r
###check utility of random slopes
model1 <- lmer(sum_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (1 | pid), data = day)
model2 <- lmer(sum_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (SM_Pos_p | pid), data = day)

anova(model1, model2)
```

```
## Data: day
## Models:
## model1: sum_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (1 | pid)
## model2: sum_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (SM_Pos_p | pid)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## model1    6 4854.2 4878.2 -2421.1   4842.2
## model2    8 4858.2 4890.2 -2421.1   4842.2     0  2          1
```

```r
model3 <- lmer(count_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (1 | pid), data = day)
model4 <- lmer(count_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (SM_Pos_p | pid), data = day)

anova(model3, model4)
```

```
## Data: day
## Models:
## model3: count_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (1 | pid)
## model4: count_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (SM_Pos_p | pid)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model3    6 4538.1 4562.1 -2263.1   4526.1
## model4    8 4542.1 4574.1 -2263.1   4526.1 0.0356  2     0.9824
```

```r
#-------------------------------------------Pos affect & same day SM----------------------------------

## Positive affect & minutes of SM

PA_on_SM_day_bayes  <- brm(sum_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (1 | pid), prior = prior1,
                    family = "gaussian", data = day, warmup = 2.5e3, iter = 1.5e4, thin = 1,
                    chains = 4, cores = 4, seed = "123",control = list(adapt_delta = 0.999, max_treedep

model_parameters(PA_on_SM_day_bayes, centrality = "mean")
```

```
## # Fixed effects
##
## Parameter    |  Mean |          95% CI |     pd | % in ROPE |  Rhat |      ESS
## ------------------------------------------------------------------------------
## (Intercept)  |  2.28 | [-25.85, 30.56] | 56.22% |    53.18% | 1.000 | 80331.00
## SM_Pos_p     |  0.24 | [ -0.31,  0.77] | 80.21% |      100% | 1.000 | 83385.00
## SM_Pos_p_c   |  0.07 | [ -0.32,  0.46] | 64.20% |      100% | 1.000 | 79000.00
## day_in_study | -0.18 | [ -1.25,  0.90] | 62.34% |      100% | 1.000 | 82131.00
##
## # Fixed effects sigma
##
## Parameter |  Mean |          95% CI |   pd | % in ROPE |  Rhat |      ESS
## -------------------------------------------------------------------------
## sigma     | 98.95 | [92.40, 106.11] | 100% |        0% | 1.000 | 80474.00
```

```r
standard_error(PA_on_SM_day_bayes)
```

```
##         Parameter         SE
## 1     b_Intercept 14.4081824
## 2      b_SM_Pos_p  0.2767788
## 3    b_SM_Pos_p_c  0.1993240
## 4 b_day_in_study  0.5510825
## 5           sigma  3.4919061
```

```r
## Positive affect & SM checks

PA_on_SM_count_day_bayes  <- brm(count_sm_p ~ SM_Pos_p + SM_Pos_p_c + day_in_study + (1 | pid), prior =
                   family = "gaussian", data = day, warmup = 2.5e3, iter = 1.5e4, thin = 1,
                   chains = 4, cores = 4, seed = "123",control = list(adapt_delta = 0.999, max_treedep


model_parameters(PA_on_SM_count_day_bayes, centrality = "mean")
```

```
## # Fixed effects
##
## Parameter    |  Mean |           95% CI |      pd | % in ROPE |  Rhat |      ESS
## --------------------------------------------------------------------------------
## (Intercept)  |  2.69 | [-16.54, 21.97] |  60.86% |    52.20% | 1.000 | 77444.00
## SM_Pos_p     |  0.75 | [  0.39,   1.12] | 100.00% |      100% | 1.000 | 79619.00
## SM_Pos_p_c   | -0.04 | [ -0.30,   0.23] |  60.84% |      100% | 1.000 | 75156.00
## day_in_study |  0.10 | [ -0.62,   0.83] |  60.95% |      100% | 1.000 | 77993.00
##
## # Fixed effects sigma
##
## Parameter |  Mean |         95% CI |   pd | % in ROPE |  Rhat |      ESS
## -------------------------------------------------------------------------
## sigma     | 66.91 | [62.53, 71.71] | 100% |        0% | 1.000 | 88627.00
```

```r
standard_error(PA_on_SM_count_day_bayes)
```

```
##         Parameter        SE
## 1     b_Intercept 9.8469461
## 2      b_SM_Pos_p 0.1876314
## 3    b_SM_Pos_p_c 0.1348922
## 4 b_day_in_study 0.3715356
## 5           sigma 2.3562323
```

Negative Affect on SM

```r
###check utility of random slopes
model1 <- lmer(sum_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid), data = day)
model2 <- lmer(sum_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (SM_Neg_p | pid), data = day)

anova(model1, model2)
```

```
## Data: day
## Models:
## model1: sum_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid)
## model2: sum_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (SM_Neg_p | pid)
##        npar  AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## model1    6 3337 3359.1 -1662.5     3325
## model2    8 3341 3370.5 -1662.5     3325     0  2          1
```

```r
summary(model1)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: sum_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid)
##    Data: day
##
## REML criterion at convergence: 3321.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2328 -0.4355 -0.0796  0.4284  5.4466
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  pid      (Intercept)    0      0.0
##  Residual             4844     69.6
## Number of obs: 294, groups:  pid, 18
##
## Fixed effects:
##              Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)   12.9225     8.8762 290.0000   1.456    0.147
## SM_Neg_p       0.2475     0.2690 290.0000   0.920    0.358
## SM_Neg_p_c    -0.2169     0.3103 290.0000  -0.699    0.485
## day_in_study  -0.5678     0.4511 290.0000  -1.259    0.209
##
## Correlation of Fixed Effects:
##             (Intr) SM_Ng_ SM_N__
## SM_Neg_p    -0.105
## SM_Neg_p_c  -0.389 -0.024
## day_in_stdy -0.725  0.145 -0.164
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

```r
model3 <- lmer(count_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid), data = day)
model4 <- lmer(count_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (SM_Neg_p | pid), data = day)

anova(model3, model4)
```

```
## Data: day
## Models:
## model3: count_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid)
## model4: count_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (SM_Neg_p | pid)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## model3    6 3318.9 3341.0 -1653.5   3306.9
## model4    8 3322.9 3352.4 -1653.5   3306.9     0  2          1
```

```r
summary(model3)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: count_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid)
##    Data: day
##
## REML criterion at convergence: 3303.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9480 -0.6185 -0.1134  0.3963  4.4539
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  pid      (Intercept)    0      0.00
##  Residual             4554     67.49
## Number of obs: 294, groups:  pid, 18
##
## Fixed effects:
##               Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)   13.08356    8.60699 290.00000   1.520   0.1296
## SM_Neg_p       0.48783    0.26085 290.00000   1.870   0.0625 .
## SM_Neg_p_c     0.09799    0.30094 290.00000   0.326   0.7449
## day_in_study  -0.60253    0.43742 290.00000  -1.377   0.1694
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) SM_Ng_ SM_N__
## SM_Neg_p    -0.105
## SM_Neg_p_c  -0.389 -0.024
## day_in_stdy -0.725  0.145 -0.164
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

```r
#--------------------------------------------Neg affect & same day SM---------------------------------

## Negative affect & minutes of SM

NA_on_SM_day_bayes  <- brm(sum_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid), prior = prior1,
                    family = "gaussian", data = day, warmup = 2.5e3, iter = 1.5e4, thin = 1,
                    chains = 4, cores = 4, seed = "123",control = list(adapt_delta = 0.999, max_treedep

model_parameters(NA_on_SM_day_bayes, centrality = "mean")
```

```
## # Fixed effects
##
## Parameter    |  Mean |         95% CI |     pd | % in ROPE |  Rhat |      ESS
## ----------------------------------------------------------------------------
## (Intercept)  | 14.74 | [-4.46, 34.73] | 93.38% |    20.11% | 1.000 | 41717.00
## SM_Neg_p     |  0.24 | [-0.28,  0.77] | 81.37% |      100% | 1.000 | 67586.00
```

```
## SM_Neg_p_c   | -0.29 | [-1.13,  0.48] | 77.07% |      100% | 1.000 | 29861.00
## day_in_study | -0.66 | [-1.57,  0.26] | 91.97% |      100% | 1.000 | 53227.00
##
## # Fixed effects sigma
##
## Parameter |  Mean |         95% CI |   pd | % in ROPE |  Rhat |      ESS
## -----------------------------------------------------------------------
## sigma     | 69.38 | [63.97, 75.42] | 100% |        0% | 1.000 | 60783.00
```

```
standard_error(NA_on_SM_day_bayes)
```

```
##          Parameter        SE
## 1      b_Intercept 9.9603126
## 2       b_SM_Neg_p 0.2687266
## 3     b_SM_Neg_p_c 0.4081199
## 4 b_day_in_study 0.4675308
## 5            sigma 2.9305403
```

```
## Negative affect & SM checks

NA_on_SM_count_day_bayes  <- brm(count_sm_p ~ SM_Neg_p + SM_Neg_p_c + day_in_study + (1 | pid), prior =
                    family = "gaussian", data = day, warmup = 2.5e3, iter = 1.5e4, thin = 1,
                    chains = 4, cores = 4, seed = "123",control = list(adapt_delta = 0.999, max_treedep

model_parameters(NA_on_SM_count_day_bayes, centrality = "mean")
```

```
## # Fixed effects
##
## Parameter    |  Mean |         95% CI |     pd | % in ROPE |  Rhat |      ESS
## -----------------------------------------------------------------------------
## (Intercept)  | 12.67 | [-4.60, 30.09] | 92.61% |    23.63% | 1.000 | 69702.00
## SM_Neg_p     |  0.49 | [-0.03,  1.00] | 96.73% |      100% | 1.000 | 64540.00
## SM_Neg_p_c   |  0.09 | [-0.56,  0.73] | 61.42% |      100% | 1.000 | 55622.00
## day_in_study | -0.62 | [-1.48,  0.24] | 91.90% |      100% | 1.000 | 63927.00
##
## # Fixed effects sigma
##
## Parameter |  Mean |         95% CI |   pd | % in ROPE |  Rhat |      ESS
## -----------------------------------------------------------------------
## sigma     | 67.64 | [62.40, 73.37] | 100% |        0% | 1.000 | 71599.00
```

```
standard_error(NA_on_SM_count_day_bayes)
```

```
##          Parameter        SE
## 1      b_Intercept 8.8099235
## 2       b_SM_Neg_p 0.2613456
## 3     b_SM_Neg_p_c 0.3279461
## 4 b_day_in_study 0.4425889
## 5            sigma 2.8079436
```