Static PID-5 and EMA Self-Compassion

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```r
# Read and process 'esi_bf' data
esi_bf <- rio::import(
  here::here(
    "data",
    "processed",
    "esi_bf.csv"
  )
) |>
  dplyr::distinct(user_id, .keep_all = TRUE) |> # Keep only distinct user_id
  dplyr::select(user_id, esi_bf) # Select relevant columns

# Read and process 'pid5' data
pid5 <- rio::import(
  here::here(
    "data",
    "processed",
    "pid5.csv"
  )
) |>
  dplyr::distinct(user_id, .keep_all = TRUE) |>  # Keep only distinct user_id
  dplyr::select(user_id, starts_with("domain_")) # Select domain variables

# Merge 'esi_bf' and 'pid5' data by user_id
df <- left_join(esi_bf, pid5, by = "user_id")

# Define list of user IDs with careless responding
user_id_with_careless_responding <- c(
  "ma_se_2005_11_14_490",
  "reve20041021036",
```

```
  "di_ma_2005_10_20_756",
  "pa_sc_2005_09_10_468",
  "il_re_2006_01_18_645",
  "so_ma_2003_10_13_804",
  "lo_ca_2005_05_07_05_437",
  "va_ma_2005_05_31_567",
  "no_un_2005_06_29_880",
  "an_bo_1988_08_24_166",
  "st_ma_2004_04_21_426",
  "an_st_2005_10_16_052",
  "vi_de_2002_12_30_067",
  "gi_ru_2005_03_08_033",
  "al_mi_2005_03_05_844",
  "la_ma_2006_01_31_787",
  "gi_lo_2004_06_27_237",
  "ch_bi_2001_01_28_407",
  "al_pe_2001_04_20_079",
  "le_de_2003_09_05_067",
  "fe_gr_2002_02_19_434",
  "ma_ba_2002_09_09_052",
  "ca_gi_2003_09_16_737",
  "an_to_2003_08_06_114",
  "al_se_2003_07_28_277",
  "ja_tr_2002_10_06_487",
  "el_ci_2002_02_15_057",
  "se_ti_2000_03_04_975",
  "co_ga_2003_10_29_614",
  "al_ba_2003_18_07_905",
  "bi_ro_2003_09_07_934",
  "an_va_2004_04_08_527",
  "ev_cr_2003_01_27_573"
)

# Filter out users with careless responses
```

```r
df1 <- df[!(df$user_id %in% user_id_with_careless_responding), ]

# Read EMA data and rename 'subj_code' to 'user_id'
ema_raw <- readRDS(
  here::here(
    "data",
    "raw",
    "ema",
    "ema_data_scoring.RDS"
  )
) |>
  dplyr::rename(
    user_id = subj_code
  )

# Merge EMA data with filtered main data
df2 <- left_join(df1, ema_raw, by = "user_id")

# Verify number of unique users
length(unique(df2$user_id))
```

```
[1] 429
```

Compliance

Escludiamo i soggetti che hanno risposto a meno di 10 notifiche.

```r
# Conta quante risposte EMA ha fornito ciascun soggetto
user_counts <- df2 %>%
  group_by(user_id) %>%
  summarise(n_responses = n()) %>%
  ungroup()

# Tieni solo i soggetti con almeno 10 risposte
valid_users <- user_counts %>%
  filter(n_responses >= 10) %>%
  pull(user_id)
```

```r
# Filtra il dataframe originale
df2 <- df2 %>%
  dplyr::filter(user_id %in% valid_users)
length(unique(df2$user_id))
```

```
[1] 379
```

Generate negative instant mood

```r
# Costruisce una misura media dell'affetto negativo momentaneo

# Seleziona solo le colonne rilevanti (per velocità)
items <- c("sad", "angry", "happy", "satisfied")

# Imputa i missing (1 solo imputazione, dato che i NA sono pochi)
imputed <- mice(df2[, items], m = 1, maxit = 10, seed = 123)
```

```
 iter imp variable
  1   1  sad  angry  happy  satisfied
  2   1  sad  angry  happy  satisfied
  3   1  sad  angry  happy  satisfied
  4   1  sad  angry  happy  satisfied
  5   1  sad  angry  happy  satisfied
  6   1  sad  angry  happy  satisfied
  7   1  sad  angry  happy  satisfied
  8   1  sad  angry  happy  satisfied
  9   1  sad  angry  happy  satisfied
  10   1  sad  angry  happy  satisfied
```

```r
# Estrai il dataset imputato e sostituisci le colonne originali
df2_imputed <- complete(imputed)
df2[, items] <- df2_imputed[, items]

df2 <- df2 %>%
  mutate(
```

```r
    happy_reversed = 100 - happy, # Scala 0-100
    satisfied_reversed = 100 - satisfied,
    neg_aff_ema = rowMeans(
      cbind(sad, angry, happy_reversed, satisfied_reversed),
      na.rm = TRUE
    )
  )
```

Self-compassion negativa

Consideriamo solo le notifiche dove Self-Compassion è stata misurata.

```r
df_self_comp_ema <- df2 %>%
  dplyr::filter(!is.na(ucs_neg) & !is.na(cs_pos))


length(unique(df_self_comp_ema$user_id))
```

```
[1] 379
```

```r
dim(df_self_comp_ema)
```

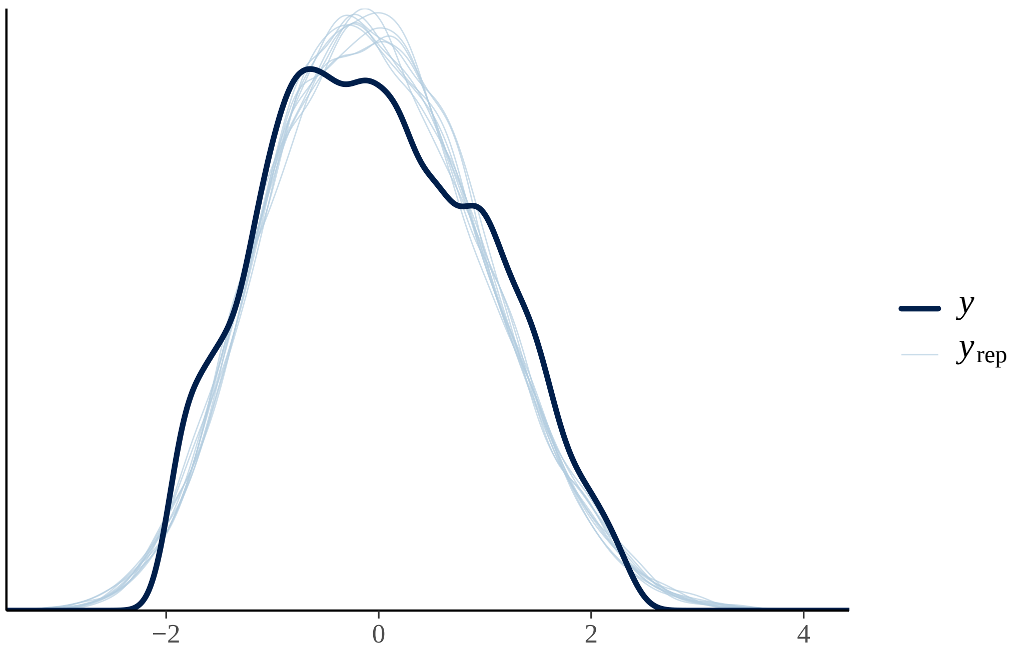
```
[1] 6229   92
```

```r
df_self_comp_ema_scaled <- df_self_comp_ema %>%
  dplyr::select(
    ucs_neg,
    domain_negative_affect,
    domain_detachment,
    domain_antagonism,
    domain_disinhibition,
    domain_psychoticism,
    neg_aff_ema,
    pid5_negative_affectivity,
    pid5_detachment,
    pid5_antagonism,
    pid5_disinhibition,
    pid5_psychoticism,
    user_id # Mantiene user_id così com'è
  ) %>%
```

```
  dplyr::mutate(
    # Applica la standardizzazione (scale) a tutte le colonne selezionate
    # tranne user_id. as.vector() è usato per assicurare che l'output sia un vettore.
    dplyr::across(
      c(
        ucs_neg,
        neg_aff_ema,
        domain_negative_affect,
        domain_detachment,
        domain_antagonism,
        domain_disinhibition,
        domain_psychoticism,
        pid5_negative_affectivity,
        pid5_detachment,
        pid5_antagonism,
        pid5_disinhibition,
        pid5_psychoticism
      ),
      ~ as.vector(scale(.))
    )
  )

model_base <- brm(
  ucs_neg ~ neg_aff_ema +
    domain_negative_affect + domain_detachment +
    domain_antagonism + domain_disinhibition + domain_psychoticism +
    (1 + neg_aff_ema | user_id),
  data = df_self_comp_ema_scaled,
  family = skew_normal(),
  prior = c(
    prior(normal(0, 1), class = "Intercept"),
    prior(normal(0, 1), class = "b"),
    prior(exponential(1), class = "sd"),
    prior(exponential(1), class = "sigma")
  ),
```

```
  chains = 4,
  cores = 4,
  iter = 2000,
  seed = 123,
  backend = "cmdstanr",
  save_pars = save_pars(all = TRUE)
)

# Posterior predictive check for the baseline model
pp_check(model_base)
```

```
Using 10 posterior draws for ppc type 'dens_overlay' by default.
```




```
print(model_base)
```

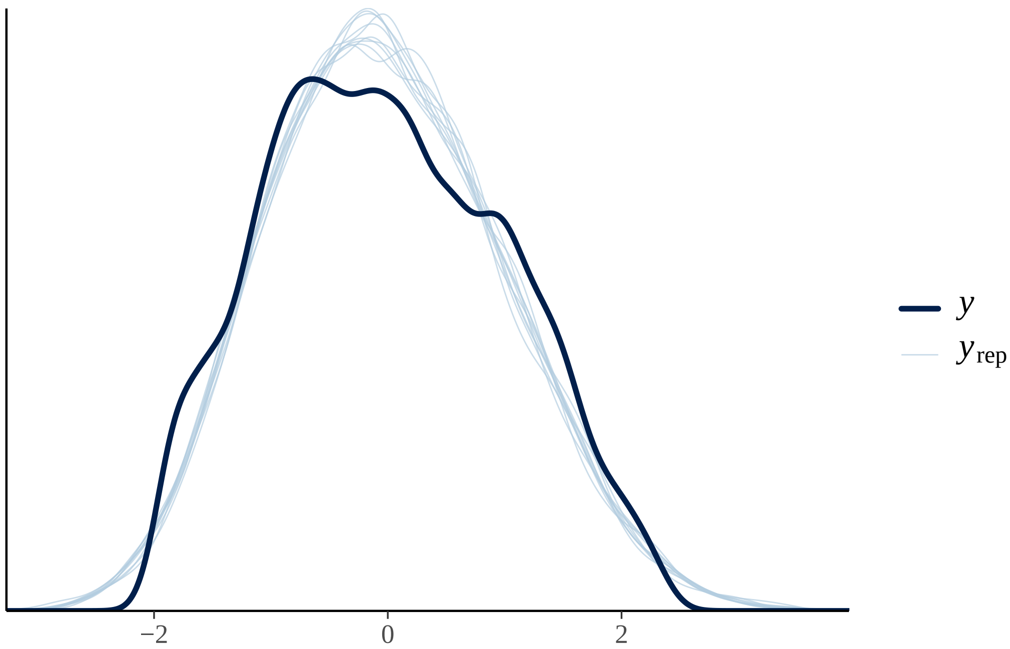
```
 Family: skew_normal
  Links: mu = identity; sigma = identity; alpha = identity
Formula: ucs_neg ~ neg_aff_ema + domain_negative_affect + domain_detachment + domain_antagon
   Data: df_self_comp_ema_scaled (Number of observations: 5757)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Multilevel Hyperparameters:
~user_id (Number of levels: 350)
```

```
                           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
sd(Intercept)                  0.52      0.02     0.48     0.57 1.00      731
sd(neg_aff_ema)                0.21      0.01     0.18     0.24 1.00     1449
cor(Intercept,neg_aff_ema)     0.16      0.08     0.00     0.31 1.00     1272
                           Tail_ESS
sd(Intercept)                  1395
sd(neg_aff_ema)                2295
cor(Intercept,neg_aff_ema)     2424

Regression Coefficients:
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
Intercept                 -0.02      0.03    -0.08     0.04 1.01      357
neg_aff_ema                0.36      0.02     0.33     0.40 1.00     2015
domain_negative_affect     0.31      0.04     0.24     0.38 1.01      467
domain_detachment          0.05      0.03    -0.01     0.12 1.01      599
domain_antagonism          0.00      0.03    -0.06     0.07 1.01      486
domain_disinhibition       0.09      0.04     0.01     0.16 1.01      558
domain_psychoticism        0.02      0.04    -0.06     0.10 1.01      546
                       Tail_ESS
Intercept                   656
neg_aff_ema                2567
domain_negative_affect     1076
domain_detachment           926
domain_antagonism           923
domain_disinhibition       1168
domain_psychoticism         981

Further Distributional Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma     0.58      0.01     0.56     0.59 1.00     4331     2848
alpha     1.28      0.11     1.05     1.49 1.00     3844     3176

Draws were sampled using sample(hmc). 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).
```

```r
# Fit augmented Bayesian model with interaction effects
model_alt <- brm(
  ucs_neg ~
    (neg_aff_ema + domain_negative_affect + domain_detachment +
       domain_antagonism + domain_disinhibition + domain_psychoticism) *
      (pid5_negative_affectivity + pid5_detachment + pid5_antagonism +
         pid5_disinhibition + pid5_psychoticism) +
    (1 + neg_aff_ema | user_id),
  data = df_self_comp_ema_scaled,
  family = skew_normal(),
  prior = c(
    prior(normal(0, 1), class = "Intercept"),
    prior(normal(0, 1), class = "b"),
    prior(exponential(1), class = "sd"),
    prior(exponential(1), class = "sigma")
  ),
  chains = 4,
  cores = 4,
  iter = 2000,
  seed = 123,
  backend = "cmdstanr",
  save_pars = save_pars(all = TRUE)
)

pp_check(model_alt)
```

```
Using 10 posterior draws for ppc type 'dens_overlay' by default.
```




```
print(model_alt)
```

```
 Family: skew_normal
  Links: mu = identity; sigma = identity; alpha = identity
Formula: ucs_neg ~ (neg_aff_ema + domain_negative_affect + domain_detachment + domain_antago
   Data: df_self_comp_ema_scaled (Number of observations: 5757)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Multilevel Hyperparameters:
~user_id (Number of levels: 350)
                           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
sd(Intercept)                  0.39      0.02     0.36     0.42 1.01     1006
sd(neg_aff_ema)                0.13      0.01     0.11     0.16 1.00     1047
cor(Intercept,neg_aff_ema)     0.24      0.10     0.04     0.43 1.00     1554
                           Tail_ESS
sd(Intercept)                  1868
sd(neg_aff_ema)                2069
cor(Intercept,neg_aff_ema)     1943

Regression Coefficients:
                                                Estimate Est.Error l-95% CI
```

Intercept	-0.03	0.02	-0.08
neg_aff_ema	0.19	0.01	0.16
domain_negative_affect	0.20	0.03	0.15
domain_detachment	0.03	0.03	-0.03
domain_antagonism	0.00	0.03	-0.05
domain_disinhibition	0.05	0.03	-0.01
domain_psychoticism	-0.01	0.03	-0.08
pid5_negative_affectivity	0.28	0.01	0.26
pid5_detachment	0.13	0.01	0.10
pid5_antagonism	-0.09	0.01	-0.12
pid5_disinhibition	0.15	0.01	0.13
pid5_psychoticism	0.04	0.02	0.01
neg_aff_ema:pid5_negative_affectivity	-0.00	0.01	-0.02
neg_aff_ema:pid5_detachment	-0.02	0.01	-0.04
neg_aff_ema:pid5_antagonism	-0.01	0.01	-0.03
neg_aff_ema:pid5_disinhibition	0.03	0.01	0.02
neg_aff_ema:pid5_psychoticism	-0.02	0.01	-0.04
domain_negative_affect:pid5_negative_affectivity	0.06	0.01	0.03
domain_negative_affect:pid5_detachment	0.02	0.01	-0.01
domain_negative_affect:pid5_antagonism	-0.02	0.01	-0.05
domain_negative_affect:pid5_disinhibition	-0.04	0.01	-0.06
domain_negative_affect:pid5_psychoticism	-0.02	0.02	-0.05
domain_detachment:pid5_negative_affectivity	0.01	0.01	-0.02
domain_detachment:pid5_detachment	-0.00	0.01	-0.03
domain_detachment:pid5_antagonism	0.01	0.01	-0.02
domain_detachment:pid5_disinhibition	-0.01	0.01	-0.03
domain_detachment:pid5_psychoticism	-0.00	0.01	-0.03
domain_antagonism:pid5_negative_affectivity	-0.00	0.01	-0.03
domain_antagonism:pid5_detachment	-0.02	0.01	-0.05
domain_antagonism:pid5_antagonism	0.03	0.01	0.01
domain_antagonism:pid5_disinhibition	-0.02	0.01	-0.04
domain_antagonism:pid5_psychoticism	-0.01	0.01	-0.03
domain_disinhibition:pid5_negative_affectivity	-0.01	0.01	-0.03
domain_disinhibition:pid5_detachment	0.00	0.01	-0.03

domain_disinhibition:pid5_antagonism	-0.02	0.01	-0.05
domain_disinhibition:pid5_disinhibition	0.02	0.01	-0.01
domain_disinhibition:pid5_psychoticism	-0.01	0.01	-0.04
domain_psychoticism:pid5_negative_affectivity	0.01	0.02	-0.02
domain_psychoticism:pid5_detachment	-0.01	0.02	-0.04
domain_psychoticism:pid5_antagonism	-0.01	0.01	-0.03
domain_psychoticism:pid5_disinhibition	0.01	0.01	-0.02
domain_psychoticism:pid5_psychoticism	0.01	0.02	-0.02

	u-95% CI	Rhat	Bulk_ESS
Intercept	0.01	1.01	689
neg_aff_ema	0.21	1.00	2272
domain_negative_affect	0.26	1.00	755
domain_detachment	0.08	1.01	481
domain_antagonism	0.05	1.00	661
domain_disinhibition	0.11	1.00	723
domain_psychoticism	0.05	1.01	485
pid5_negative_affectivity	0.31	1.00	3004
pid5_detachment	0.16	1.00	3156
pid5_antagonism	-0.07	1.00	2915
pid5_disinhibition	0.17	1.00	3902
pid5_psychoticism	0.07	1.00	2931
neg_aff_ema:pid5_negative_affectivity	0.02	1.00	3792
neg_aff_ema:pid5_detachment	-0.00	1.00	3517
neg_aff_ema:pid5_antagonism	0.01	1.00	4201
neg_aff_ema:pid5_disinhibition	0.05	1.00	3971
neg_aff_ema:pid5_psychoticism	0.01	1.00	3551
domain_negative_affect:pid5_negative_affectivity	0.08	1.00	2855
domain_negative_affect:pid5_detachment	0.05	1.00	2256
domain_negative_affect:pid5_antagonism	0.01	1.00	2770
domain_negative_affect:pid5_disinhibition	-0.01	1.00	3479
domain_negative_affect:pid5_psychoticism	0.02	1.00	2156
domain_detachment:pid5_negative_affectivity	0.04	1.00	3000
domain_detachment:pid5_detachment	0.03	1.00	2743
domain_detachment:pid5_antagonism	0.03	1.00	2991

```
domain_detachment:pid5_disinhibition               0.02 1.00     3364
domain_detachment:pid5_psychoticism                0.02 1.00     2538
domain_antagonism:pid5_negative_affectivity        0.02 1.00     2562
domain_antagonism:pid5_detachment                  0.00 1.00     2769
domain_antagonism:pid5_antagonism                  0.06 1.00     2740
domain_antagonism:pid5_disinhibition               0.01 1.00     3406
domain_antagonism:pid5_psychoticism                0.02 1.00     2748
domain_disinhibition:pid5_negative_affectivity     0.02 1.00     2799
domain_disinhibition:pid5_detachment               0.03 1.00     2435
domain_disinhibition:pid5_antagonism              -0.00 1.00     3241
domain_disinhibition:pid5_disinhibition            0.04 1.00     3537
domain_disinhibition:pid5_psychoticism             0.02 1.00     2704
domain_psychoticism:pid5_negative_affectivity      0.04 1.00     2228
domain_psychoticism:pid5_detachment                0.02 1.00     2184
domain_psychoticism:pid5_antagonism                0.02 1.00     2766
domain_psychoticism:pid5_disinhibition             0.04 1.00     3107
domain_psychoticism:pid5_psychoticism              0.04 1.00     2278
                                               Tail_ESS
Intercept                                          1542
neg_aff_ema                                        3434
domain_negative_affect                             1384
domain_detachment                                  1055
domain_antagonism                                  1420
domain_disinhibition                               1438
domain_psychoticism                                1048
pid5_negative_affectivity                          2991
pid5_detachment                                    3020
pid5_antagonism                                    3262
pid5_disinhibition                                 3392
pid5_psychoticism                                  2676
neg_aff_ema:pid5_negative_affectivity              3398
neg_aff_ema:pid5_detachment                        2727
neg_aff_ema:pid5_antagonism                        3087
neg_aff_ema:pid5_disinhibition                     3185
```

```
neg_aff_ema:pid5_psychoticism                      3221
domain_negative_affect:pid5_negative_affectivity     3292
domain_negative_affect:pid5_detachment             3138
domain_negative_affect:pid5_antagonism             2935
domain_negative_affect:pid5_disinhibition          2941
domain_negative_affect:pid5_psychoticism           2969
domain_detachment:pid5_negative_affectivity        2873
domain_detachment:pid5_detachment                  3118
domain_detachment:pid5_antagonism                  3143
domain_detachment:pid5_disinhibition               2914
domain_detachment:pid5_psychoticism                2816
domain_antagonism:pid5_negative_affectivity        2666
domain_antagonism:pid5_detachment                  3164
domain_antagonism:pid5_antagonism                  3109
domain_antagonism:pid5_disinhibition               3514
domain_antagonism:pid5_psychoticism                2884
domain_disinhibition:pid5_negative_affectivity     2992
domain_disinhibition:pid5_detachment               2897
domain_disinhibition:pid5_antagonism               3189
domain_disinhibition:pid5_disinhibition            2794
domain_disinhibition:pid5_psychoticism             2991
domain_psychoticism:pid5_negative_affectivity      2745
domain_psychoticism:pid5_detachment                2840
domain_psychoticism:pid5_antagonism                3363
domain_psychoticism:pid5_disinhibition             2770
domain_psychoticism:pid5_psychoticism              2468

Further Distributional Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma     0.53      0.01     0.52     0.54 1.00     4476     2921
alpha     1.20      0.11     0.97     1.42 1.00     2977     2787

Draws were sampled using sample(hmc). 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).
```

```r
loo0 <- loo(model_base, save_psis = TRUE)
```

```
Warning: Found 10 observations with a pareto_k > 0.7 in model 'model_base'. We
recommend to set 'moment_match = TRUE' in order to perform moment matching for
problematic observations.
```

```r
loo1 <- loo(model_alt, save_psis = TRUE)
```

```
Warning: Found 6 observations with a pareto_k > 0.7 in model 'model_alt'. We
recommend to set 'moment_match = TRUE' in order to perform moment matching for
problematic observations.
```

```r
loo_compare(loo0, loo1)
```

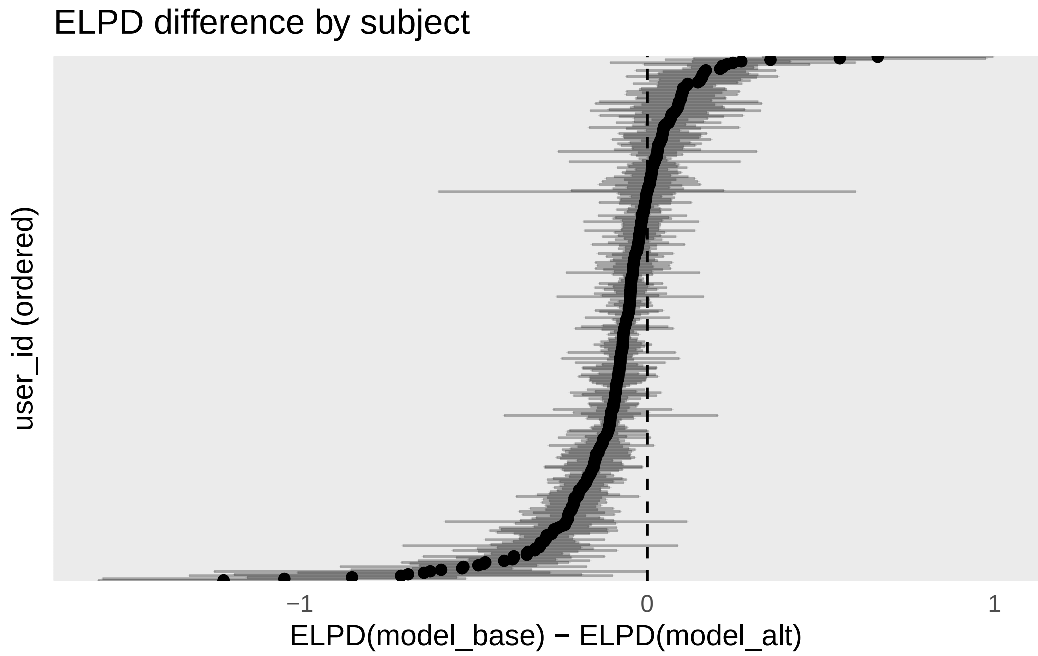
```
           elpd_diff se_diff
model_alt     0.0       0.0
model_base -472.9      42.1
```

Visualizzare ELPD_diff

Visualizzare dove il modello alternativo (model_alt) migliora la predizione rispetto al modello di base (model_base), a livello di soggetto.

```r
# Differenza pointwise tra i due modelli
elpd_diff <- loo0$pointwise[, "elpd_loo"] - loo1$pointwise[, "elpd_loo"]

# Recupera i dati usati nel modello
model_data <- model_base$data


# Aggiungi la colonna con la differenza di ELPD
model_data$elpd_diff <- elpd_diff

subject_diffs <- model_data %>%
  group_by(user_id) %>%
  summarise(
    mean_elpd_diff = mean(elpd_diff, na.rm = TRUE),
    se = sd(elpd_diff, na.rm = TRUE) / sqrt(n())
  ) %>%
  arrange(mean_elpd_diff)
```

```r
ggplot(subject_diffs, aes(x = reorder(user_id, mean_elpd_diff), y = mean_elpd_diff)) +
  geom_point() +
  geom_errorbar(aes(ymin = mean_elpd_diff - se, ymax = mean_elpd_diff + se),
                width = 0.2, alpha = 0.3) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  coord_flip() +
  labs(title = "ELPD difference by subject",
       x = "user_id (ordered)",
       y = "ELPD(model_base) - ELPD(model_alt)") +
  theme_minimal() +
  scale_x_discrete(labels = NULL)
```



Ogni punto rappresenta un soggetto. L'asse y mostra la differenza di ELPD tra i modelli: ELPD_base − ELPD_alt. I valori sotto lo zero indicano che il modello alternativo predice meglio per quel soggetto. Le barre di errore indicano l'incertezza (errore standard) per ciascun soggetto. Nel caso presente, dato il valore complessivo di elpd_diff = -466, ci aspettiamo che la maggior parte dei soggetti abbia valori negativi.

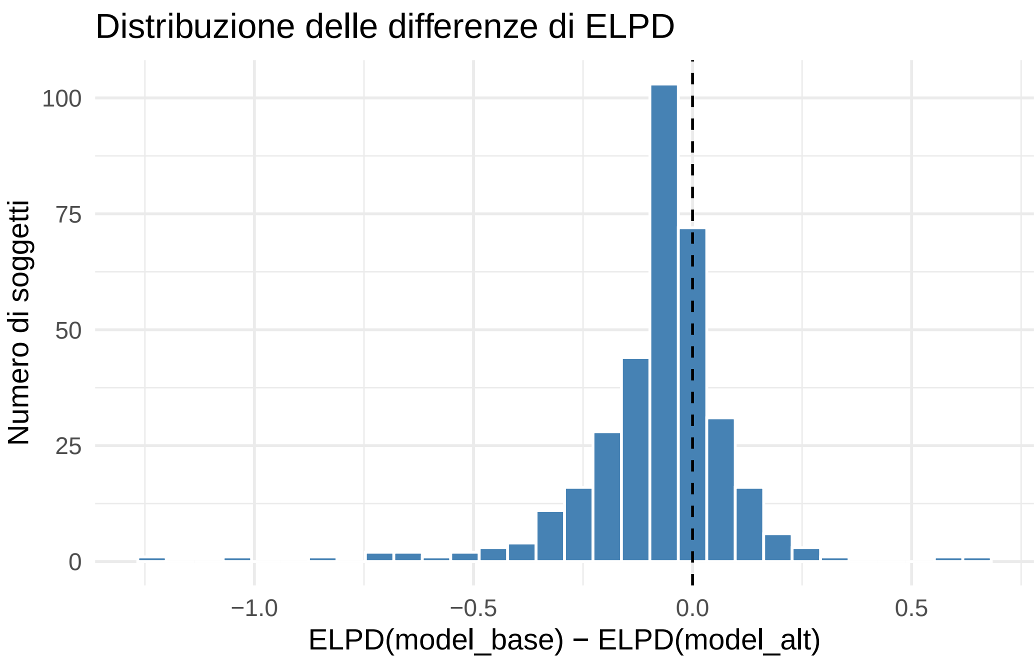
```r
subject_diffs %>%
  summarise(
    n = n(),
    n_better_alt = sum(mean_elpd_diff < 0),
    proportion = n_better_alt / n,
```

```r
    percent = proportion * 100
  )
```

```
# A tibble: 1 x 4
      n n_better_alt proportion percent
  <int>        <int>      <dbl>   <dbl>
1   350          259       0.74      74
```

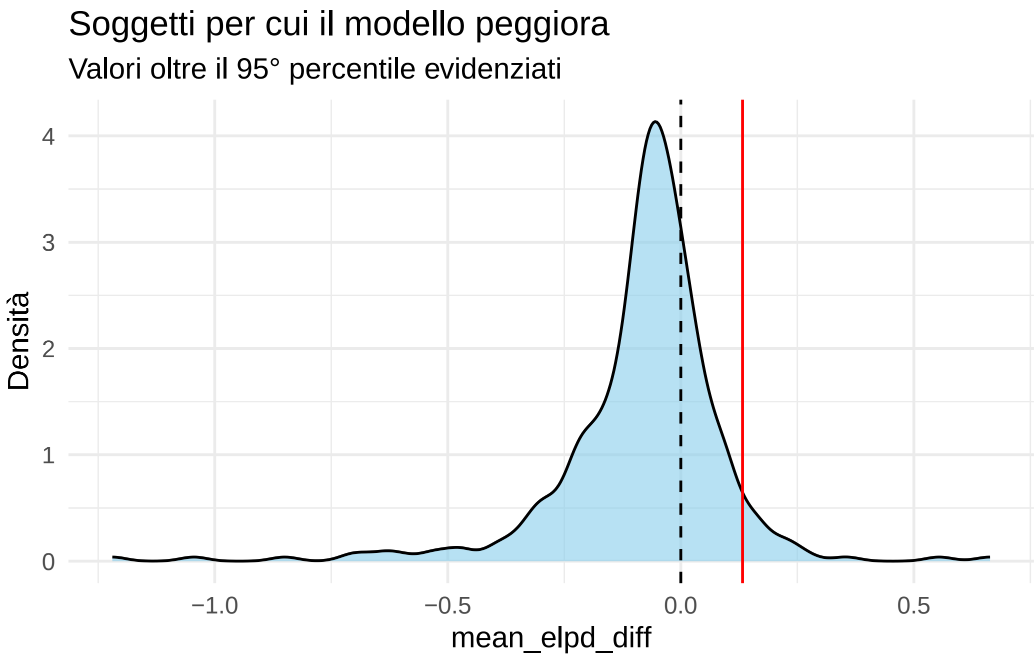
Il 74% dei soggetti mostrano una migliore predizione con il modello alternativo rispetto al modello base. La preferenza per model_alt è quindi generalizzata, non guidata da pochi individui.

```r
ggplot(subject_diffs, aes(x = mean_elpd_diff)) +
  geom_histogram(bins = 30, fill = "steelblue", color = "white") +
  geom_vline(xintercept = 0, linetype = "dashed") +
  labs(
    title = "Distribuzione delle differenze di ELPD",
    x = "ELPD(model_base) - ELPD(model_alt)",
    y = "Numero di soggetti"
  ) +
  theme_minimal()
```




```r
ggplot(subject_diffs, aes(x = mean_elpd_diff)) +
  geom_density(fill = "skyblue", alpha = 0.6) +
  geom_vline(xintercept = 0, linetype = "dashed") +
```

```r
  geom_vline(xintercept = quantile(subject_diffs$mean_elpd_diff, 0.95), color = "red") +
  labs(title = "Soggetti per cui il modello peggiora",
       subtitle = "Valori oltre il 95° percentile evidenziati",
       x = "mean_elpd_diff", y = "Densità") +
  theme_minimal()
```




```r
bayes_R2(model_base)
```

```
    Estimate   Est.Error      Q2.5     Q97.5
R2 0.6737922 0.004505675 0.6644835 0.6823353
```

```r
bayes_R2(model_alt)
```

```
    Estimate   Est.Error      Q2.5     Q97.5
R2 0.7223872 0.003729268 0.7150448 0.7297639
```

```r
# K-fold cross-validation (e.g., 10 folds)
# kfold_base <- kfold(model_base, K = 5, seed = 123)
# kfold_alt  <- kfold(model_alt,  K = 5, seed = 123)
# kfold_compare(kfold_base, kfold_alt)
# Se elpd_diff è negativo per model_base, vuol dire che model_alt predice meglio
# anche in validazione k-fold.

subject_diffs <- subject_diffs %>%
  mutate(benefit_score = scale(-mean_elpd_diff))
```

```
# valori alti = miglioramento maggiore
subject_diffs
```

```
# A tibble: 350 x 4
   user_id              mean_elpd_diff    se benefit_score[,1]
   <chr>                         <dbl> <dbl>             <dbl>
 1 so_li_2004_10_29_776          -1.22  0.361             6.37
 2 ch_va_2003_04_08_010          -1.04  0.524             5.39
 3 el_ca_2003_06_14_053          -0.850 0.303             4.30
 4 mi_lo_2005_03_17_960          -0.709 0.610             3.51
 5 gi_ma_2004_01_10_447          -0.689 0.501             3.40
 6 ca_fo_2002_08_30_071          -0.643 0.364             3.14
 7 an_gr_2003_02_23_266          -0.625 0.622             3.04
 8 al_ne_2005_11_07_247          -0.593 0.261             2.87
 9 an_ba_2003_04_19_988          -0.533 0.145             2.53
10 ir_mo_2005_02_23_157          -0.529 0.355             2.51
# i 340 more rows
```

Discussione dei risultati: impatto delle misure dinamiche sui modelli predittivi

L'obiettivo principale di questa analisi era valutare se l'integrazione delle **misure dinamiche dei tratti disadattivi di personalità** (ovvero, le valutazioni settimanali del PID-5 tramite EMA) migliorasse la capacità di prevedere l'intensità della **self-compassion negativa** in risposta ad affetti negativi momentanei.

Per testare questa ipotesi, abbiamo confrontato due modelli:

- un **modello base**, in cui la self-compassion negativa (UCS) era spiegata da indicatori EMA dell'affetto negativo e dai tratti PID-5 valutati una sola volta all'inizio dello studio;
- un **modello alternativo**, in cui gli stessi predittori interagivano con le **misure EMA dei cinque domini PID-5**, raccolte in parallelo ai dati di affetto negativo.

I risultati dell'analisi bayesiana con confronto via ELPD (Expected Log Predictive Density) indicano un chiaro miglioramento nella predizione per il modello che include le **interazioni con i tratti EMA**. In particolare, la differenza complessiva di ELPD tra i modelli è di **ΔELPD = -466**, a favore del modello alternativo. Questo effetto non è guidato da pochi casi estremi: in oltre il **74% dei soggetti**, il modello con i tratti EMA ha fornito predizioni migliori, e la distribuzione soggetto-specifica delle differenze di ELPD è fortemente sbilanciata a favore del modello dinamico.

Anche la **varianza spiegata a posteriori (Bayes R^2)** è maggiore nel modello alternativo ($R^2 = 0.52$ vs. 0.41), suggerendo che la variabilità intra-individuale nei tratti di personalità è un moderatore cruciale della reattività affettiva momentanea.

Dal punto di vista teorico, questi risultati forniscono supporto all'ipotesi che la relazione tra affetto negativo e self-compassion negativa non sia una funzione stabile e fissa, ma **una funzione modulata dai tratti di personalità così come si esprimono nel momento**. L'uso delle misure EMA del PID-5 cattura queste **fluttuazioni disposizionali contestuali**, che non sono accessibili tramite la sola somministrazione statica del PID-5 a inizio studio.

In linea con un approccio **idionomico**, che mira a comprendere il funzionamento individuale nel suo contesto situato, l'evidenza raccolta suggerisce che **combinare misure di stato (affetto negativo momentaneo) con misure di tratto dinamiche (PID-5 EMA)** permette una modellazione più sensibile delle vulnerabilità psicopatologiche. Questi risultati rafforzano l'idea che le valutazioni EMA non siano semplicemente misure rumorose, ma rappresentino un valore aggiunto per comprendere **quando** e **per chi** si attivano risposte maladattive, come la self-compassion negativa.