

Static PID-5 and EMA Self-Compassion

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Le misure “basali” corrispondenti ai 5 domini del PID-5 sono state calcolate **escludendo** i 15 item che vengono usati nelle notifiche EMA.

```
# 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
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.

```

# 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)

# Filtra il dataframe originale
df2 <- df2 %>%
  dplyr::filter(user_id %in% valid_users)

length(unique(df2$user_id))

[1] 379

```

Generate negative instant mood

```

# 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

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

df2 <- df2 %>%
  mutate(
    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.

```
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

dim(df_self_comp_ema)

[1] 6229    92

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 +
```

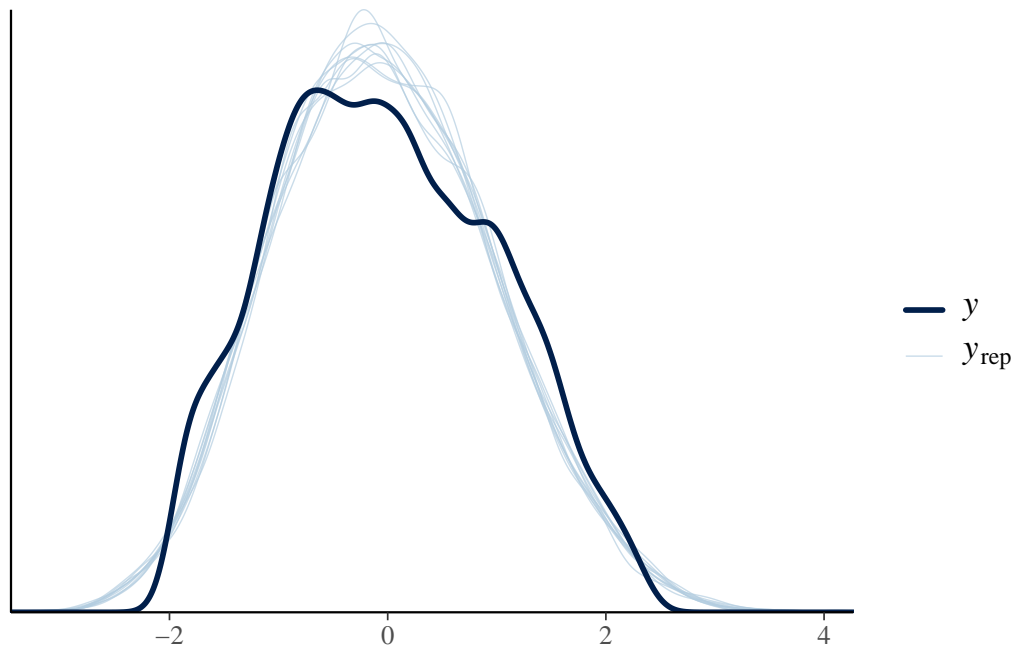
```

    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_antagonism + domain_disinhibition + domain_psychoticism
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	0.56	1.00	675
sd(neg_aff_ema)	0.21	0.02	0.18	0.24	1.00	1281
cor(Intercept,neg_aff_ema)	0.15	0.08	-0.01	0.30	1.00	970
	Tail_ESS					
sd(Intercept)	1509					
sd(neg_aff_ema)	2646					
cor(Intercept,neg_aff_ema)	1932					

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	367
neg_aff_ema	0.36	0.02	0.33	0.39	1.00	1525
domain_negative_affect	0.32	0.04	0.25	0.39	1.01	426
domain_detachment	0.05	0.03	-0.01	0.12	1.00	492
domain_antagonism	0.01	0.03	-0.06	0.07	1.01	383
domain_disinhibition	0.09	0.04	0.02	0.16	1.01	476
domain_psychoticism	0.01	0.04	-0.08	0.09	1.01	387
	Tail_ESS					
Intercept	641					
neg_aff_ema	2500					
domain_negative_affect	1075					
domain_detachment	1094					
domain_antagonism	784					
domain_disinhibition	921					
domain_psychoticism	630					

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	4834	3022
alpha	1.28	0.11	1.05	1.50	1.00	3136	3110

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).

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")
  )
)
```

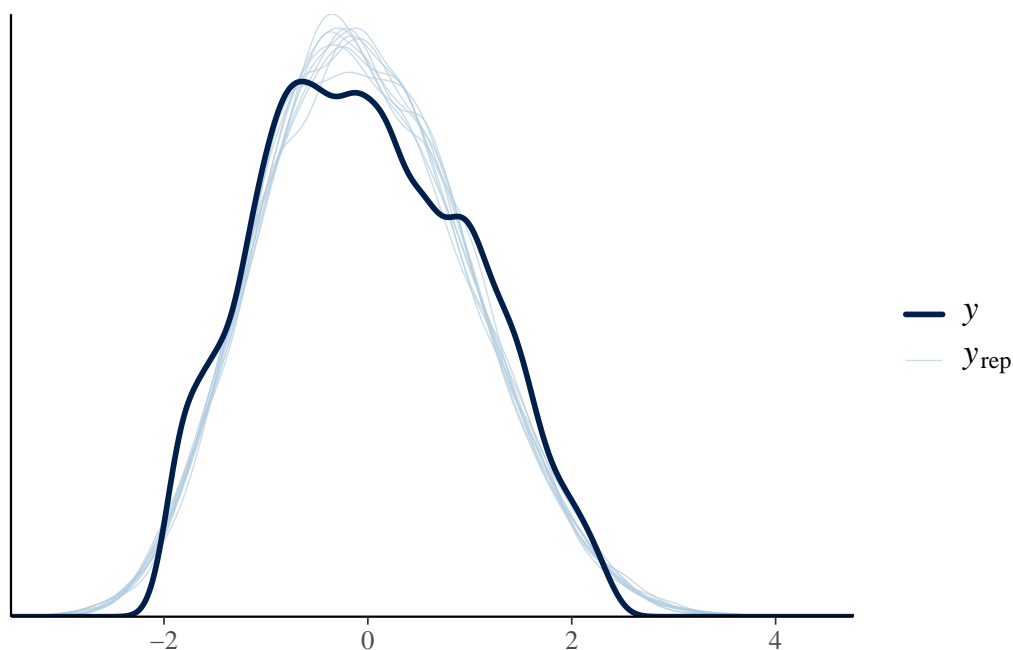
```

),
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_antag
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	0.35	0.42	1.00	978
sd(neg_aff_ema)	0.13	0.01	0.10	0.16	1.00	1318
cor(Intercept,neg_aff_ema)	0.23	0.10	0.04	0.41	1.00	1915
	Tail_ESS					
sd(Intercept)	1602					
sd(neg_aff_ema)	2170					
cor(Intercept,neg_aff_ema)	2860					

Regression Coefficients:

	Estimate	Est.Error	1-95% CI
Intercept	-0.03	0.02	-0.08
neg_aff_ema	0.19	0.01	0.16
domain_negative_affect	0.21	0.03	0.15
domain_detachment	0.03	0.03	-0.02
domain_antagonism	0.00	0.03	-0.05
domain_disinhibition	0.05	0.03	-0.01
domain_psychoticism	-0.02	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	-0.01	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	-0.03	0.01	-0.06
domain_negative_affect:pid5_psychoticism	-0.02	0.02	-0.05
domain_detachment:pid5_negative_affectivity	0.01	0.01	-0.01
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	-0.04
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	-0.00	0.01	-0.03
domain_psychoticism:pid5_disinhibition	0.01	0.02	-0.02
domain_psychoticism:pid5_psychoticism	0.01	0.02	-0.02
	u-95% CI	Rhat	Bulk_ESS
Intercept	0.02	1.01	722
neg_aff_ema	0.21	1.00	2825
domain_negative_affect	0.27	1.00	640
domain_detachment	0.08	1.01	637
domain_antagonism	0.05	1.02	599
domain_disinhibition	0.10	1.01	684
domain_psychoticism	0.04	1.00	765

pid5_negative_affectivity	0.31	1.00	3291
pid5_detachment	0.16	1.00	2747
pid5_antagonism	-0.07	1.00	3048
pid5_disinhibition	0.17	1.00	3360
pid5_psychoticism	0.06	1.00	3028
neg_aff_ema:pid5_negative_affectivity	0.02	1.00	2959
neg_aff_ema:pid5_detachment	-0.00	1.00	4052
neg_aff_ema:pid5_antagonism	0.01	1.00	3919
neg_aff_ema:pid5_disinhibition	0.05	1.00	4263
neg_aff_ema:pid5_psychoticism	0.01	1.00	3163
domain_negative_affect:pid5_negative_affectivity	0.08	1.00	2659
domain_negative_affect:pid5_detachment	0.05	1.00	2712
domain_negative_affect:pid5_antagonism	0.00	1.00	3231
domain_negative_affect:pid5_disinhibition	-0.01	1.00	3573
domain_negative_affect:pid5_psychoticism	0.02	1.00	2406
domain_detachment:pid5_negative_affectivity	0.04	1.00	2468
domain_detachment:pid5_detachment	0.03	1.00	2825
domain_detachment:pid5_antagonism	0.03	1.00	3485
domain_detachment:pid5_disinhibition	0.02	1.00	3260
domain_detachment:pid5_psychoticism	0.02	1.00	2815
domain_antagonism:pid5_negative_affectivity	0.02	1.00	2785
domain_antagonism:pid5_detachment	0.00	1.00	2496
domain_antagonism:pid5_antagonism	0.06	1.00	2756
domain_antagonism:pid5_disinhibition	0.01	1.00	3556
domain_antagonism:pid5_psychoticism	0.02	1.00	2712
domain_disinhibition:pid5_negative_affectivity	0.02	1.00	2792
domain_disinhibition:pid5_detachment	0.03	1.00	2828
domain_disinhibition:pid5_antagonism	-0.00	1.00	3266
domain_disinhibition:pid5_disinhibition	0.04	1.00	3486
domain_disinhibition:pid5_psychoticism	0.02	1.00	3082
domain_psychoticism:pid5_negative_affectivity	0.04	1.00	2214
domain_psychoticism:pid5_detachment	0.02	1.00	2664
domain_psychoticism:pid5_antagonism	0.02	1.00	2428
domain_psychoticism:pid5_disinhibition	0.04	1.00	2845
domain_psychoticism:pid5_psychoticism	0.04	1.00	2246

Tail_ESS

Intercept	1312
neg_aff_ema	3241
domain_negative_affect	1249
domain_detachment	1367
domain_antagonism	1116
domain_disinhibition	1268
domain_psychoticism	1510
pid5_negative_affectivity	3625
pid5_detachment	3248
pid5_antagonism	2582
pid5_disinhibition	3169
pid5_psychoticism	3049
neg_aff_ema:pid5_negative_affectivity	2924
neg_aff_ema:pid5_detachment	3159
neg_aff_ema:pid5_antagonism	3311

neg_aff_ema:pid5_disinhibition	3167
neg_aff_ema:pid5_psychoticism	3000
domain_negative_affect:pid5_negative_affectivity	2427
domain_negative_affect:pid5_detachment	3237
domain_negative_affect:pid5_antagonism	3026
domain_negative_affect:pid5_disinhibition	3109
domain_negative_affect:pid5_psychoticism	2961
domain_detachment:pid5_negative_affectivity	2975
domain_detachment:pid5_detachment	3483
domain_detachment:pid5_antagonism	3088
domain_detachment:pid5_disinhibition	2828
domain_detachment:pid5_psychoticism	3004
domain_antagonism:pid5_negative_affectivity	2687
domain_antagonism:pid5_detachment	2927
domain_antagonism:pid5_antagonism	3124
domain_antagonism:pid5_disinhibition	3162
domain_antagonism:pid5_psychoticism	3055
domain_disinhibition:pid5_negative_affectivity	3277
domain_disinhibition:pid5_detachment	3223
domain_disinhibition:pid5_antagonism	3161
domain_disinhibition:pid5_disinhibition	3222
domain_disinhibition:pid5_psychoticism	3184
domain_psychoticism:pid5_negative_affectivity	2867
domain_psychoticism:pid5_detachment	2920
domain_psychoticism:pid5_antagonism	2981
domain_psychoticism:pid5_disinhibition	3168
domain_psychoticism:pid5_psychoticism	2878

Further Distributional Parameters:

	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	0.53	0.01	0.52	0.54	1.00	4865	2944
alpha	1.20	0.11	0.98	1.42	1.00	3705	3458

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).

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

Warning: Found 13 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.

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

Warning: Found 5 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.

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

	elpd_diff	se_diff
model_alt	0.0	0.0
model_base	-475.1	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.

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

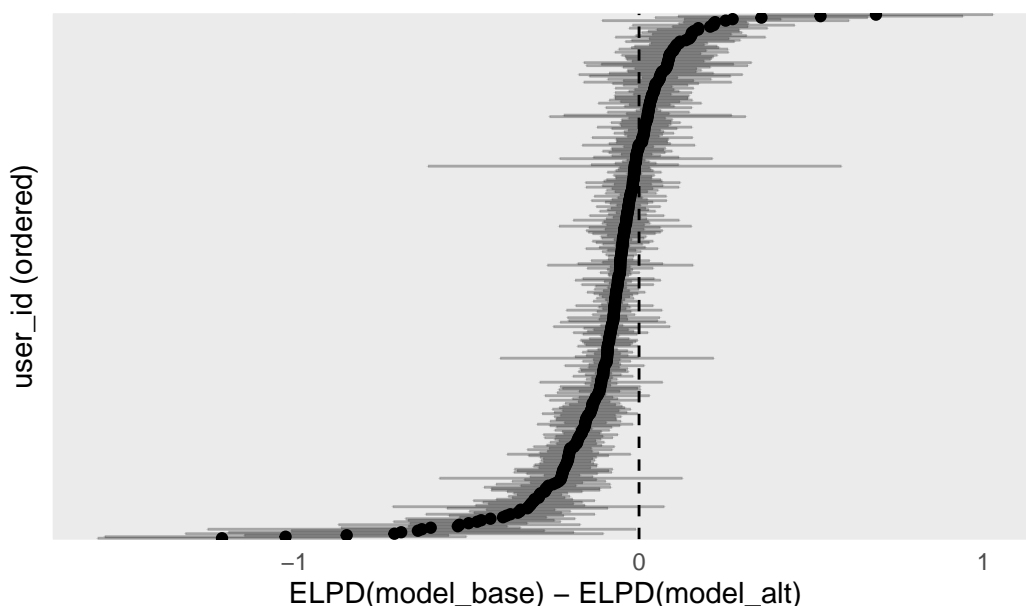
# Recupera i dati usati nel modello
model_data <- model_base$data

# 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)

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)
```

ELPD difference by subject



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.

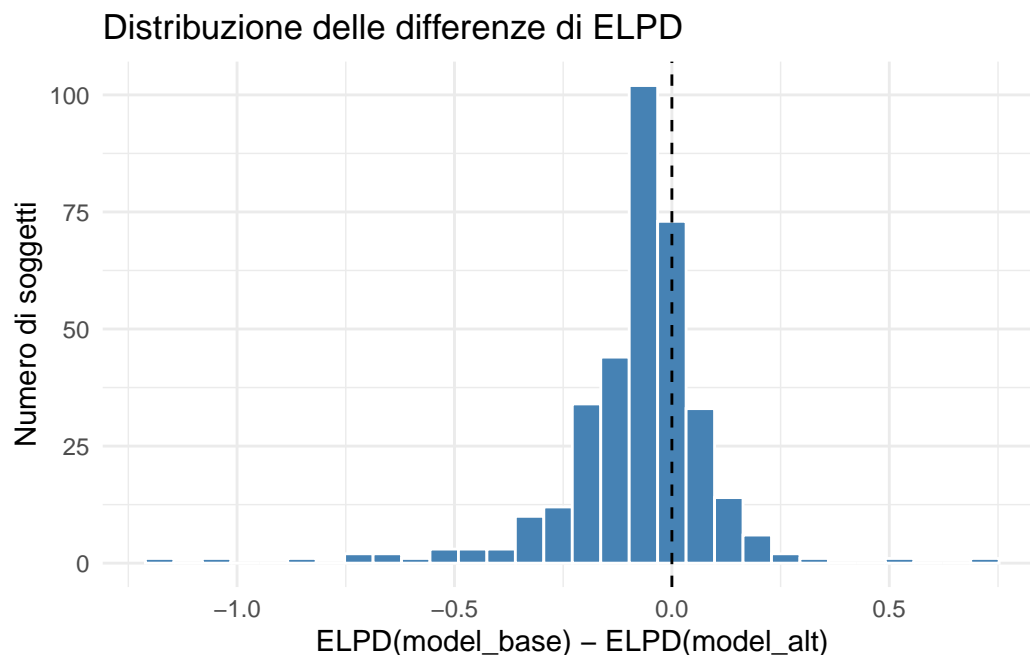
```
subject_diffs %>%
  summarise(
    n = n(),
    n_better_alt = sum(mean_elpd_diff < 0),
    proportion = n_better_alt / n,
    percent = proportion * 100
  )
```

A tibble: 1 x 4

	n	n_better_alt	proportion	percent
	<int>	<int>	<dbl>	<dbl>
1	350	263	0.751	75.1

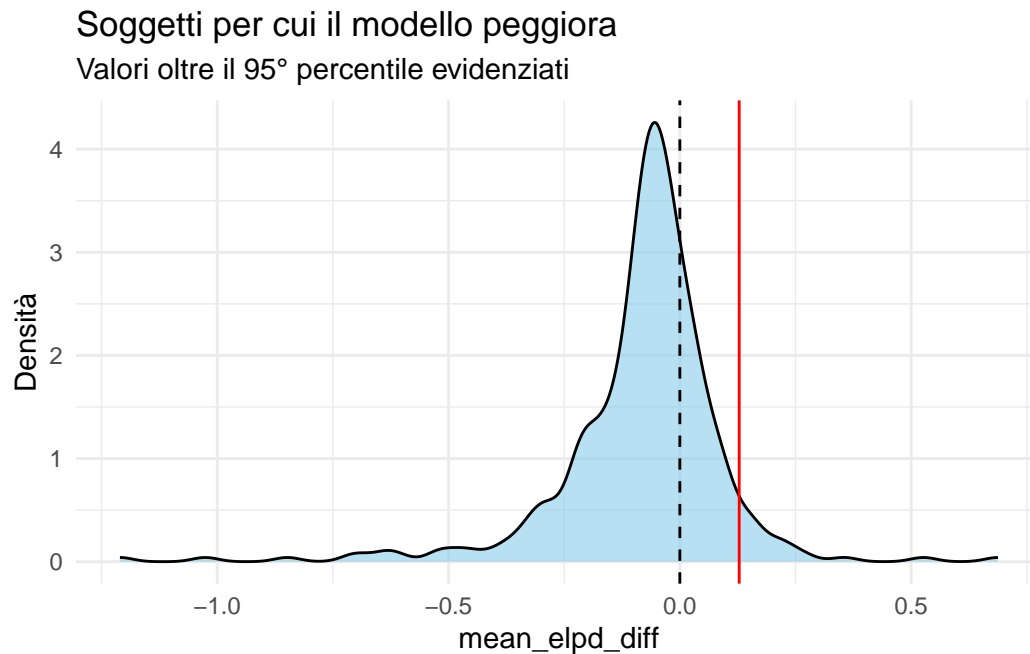
Il 74% dei soggetti mostrano una migliore predizione con il modello alternativo rispetto al modello base. La preferenza per `model_alt` è quindi generalizzata, non guidata da pochi individui.

```
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()
```



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

```
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()
```



```
bayes_R2(model_base)
```

```
      Estimate Est.Error    Q2.5    Q97.5
R2 0.6737499 0.004462602 0.6649309 0.6821722
```

```
bayes_R2(model_alt)
```

```
      Estimate Est.Error    Q2.5    Q97.5
R2 0.7224773 0.003742531 0.7149858 0.7297672
```

```
# 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	-1.21	0.361	6.35
2	ch_va_2003_04_08_010	-1.03	0.525	5.31
3	el_ca_2003_06_14_053	-0.849	0.297	4.32
4	mi_lo_2005_03_17_960	-0.710	0.607	3.54

5 gi_ma_2004_01_10_447	-0.690 0.502	3.42
6 ca_fo_2002_08_30_071	-0.642 0.368	3.15
7 an_gr_2003_02_23_266	-0.630 0.622	3.09
8 al_ne_2005_11_07_247	-0.605 0.261	2.94
9 an_ba_2003_04_19_988	-0.526 0.144	2.50
10 ir_mo_2005_02_23_157	-0.521 0.351	2.47

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 $\Delta\text{ELPD} = -466$, 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.