

# THE HIERARCHICAL STRUCTURE OF AFFECT

Frederico Pedrosa

2025-12-19

## Contents

<b>1</b>	<b>Environment Setup</b>	<b>2</b>
<b>2</b>	<b>Estimates with embeddings</b>	<b>2</b>
2.1	Load embeddings and transpose matrix to 768 x 45 . . . . .	2
2.2	Verify if the matrix is factorable . . . . .	4
2.3	Horn's Parallel Analysis for Principal Components and Factor Analysis . . . . .	5
2.4	PCA - General Factor Identification . . . . .	8
2.5	General factor extraction reveals the circumplex model . . . . .	10
2.6	PCA with Varimax to better identify words representing PCs . . . . .	11
2.7	Formative vs. Reflective . . . . .	13
2.8	Formative second-order . . . . .	14
2.9	Reflective second-order . . . . .	18
2.10	Reflective via lavaan . . . . .	22
2.11	Study 1 Correlations . . . . .	25
<b>3</b>	<b>Estimates with PANAS</b>	<b>27</b>
3.1	Factorability . . . . .	28
3.2	Horn's Parallel Analysis . . . . .	29
3.3	Parallel Analysis Plot . . . . .	30
3.4	PANAS PCA . . . . .	31
3.5	Plot . . . . .	34
3.6	With rotation to extract components . . . . .	35
3.7	Formative vs. Reflective - PANAS . . . . .	37
3.8	Formative - PANAS . . . . .	38
3.9	Reflective with lavaan . . . . .	41
3.10	Reflective bifactor model fits the data better . . . . .	46
3.11	Constrained bifactor model . . . . .	50

3.12 Second-order model test . . . . .	54
3.13 Better model plot . . . . .	59
3.14 Study 2 Correlations . . . . .	60
3.15 Bifactor model with specific factors covarying vs. previous bifactor model . . . . .	62

# 1 Environment Setup

```
if (!require("pacman")) {
  install.packages("pacman")
}
```

```
## Carregando pacotes exigidos: pacman
```

```
# Step 2: Use pacman's p_load() function to install (if necessary) and load all packages.
# You only need to list the package names without quotes.
```

```
pacman::p_load(
  # Data Reading and Manipulation
  readr, readxl, dplyr, tidyr, janitor, stringi, stringr, tidytext,

  # Factor Analysis and Psychometrics
  psych, EFA.dimensions, GPArotation, MVN,

  # Structural Equation Modeling
  lavaan, semTools, semnr, cSEM,

  # Network Analysis
  EGAnet,

  # Data Visualization
  ggplot2, patchwork, ggrepel, GGally, semPlot, plotly
)

# Confirmation message
cat("All necessary packages have been verified and loaded successfully.")
```

```
## All necessary packages have been verified and loaded successfully.
```

## 2 Estimates with embeddings

### 2.1 Load embeddings and transpose matrix to 768 x 45

```
data <- read_csv("embeddings_circumplex.csv")
```

```
## Rows: 45 Columns: 769
```

```
## -- Column specification -----
```

```
## Delimiter: ","
## chr (1): palavra
## dbl (768): dim_1, dim_2, dim_3, dim_4, dim_5, dim_6, dim_7, dim_8, dim_9, di...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
cat("Original file dimensions (Rows x Columns):", dim(data), "\n")
```

```
## Original file dimensions (Rows x Columns): 45 769
```

```
print("First rows of the original file:")
```

```
## [1] "First rows of the original file:"
```

```
print(head(data))
```

```
## # A tibble: 6 x 769
##   palavra    dim_1 dim_2    dim_3    dim_4 dim_5    dim_6    dim_7    dim_8
##   <chr>      <dbl> <dbl>    <dbl>    <dbl> <dbl>    <dbl>    <dbl>    <dbl>
## 1 foda      -0.0177 0.0514 -0.0165  0.0392  0.0824  0.0450 -0.00317 -0.0190
## 2 grande   -0.0474 0.0904 -0.0152  0.0436  0.102  -0.00491 -0.0896 -0.0344
## 3 saudade  -0.0177 0.125  -0.0155 -0.00331 0.105  0.0108 -0.0563 -0.0258
## 4 merda     0.0104 0.0927 -0.0157  0.0430  0.0844  0.0552  0.0201 -0.0119
## 5 bons     -0.0502 0.109  -0.0152  0.000375 0.0937 -0.00222 -0.0901 -0.0242
## 6 descanse -0.0687 0.179  -0.0157  0.0744  0.103  -0.0347 -0.0802  0.0179
## # i 760 more variables: dim_9 <dbl>, dim_10 <dbl>, dim_11 <dbl>, dim_12 <dbl>,
## #   dim_13 <dbl>, dim_14 <dbl>, dim_15 <dbl>, dim_16 <dbl>, dim_17 <dbl>,
## #   dim_18 <dbl>, dim_19 <dbl>, dim_20 <dbl>, dim_21 <dbl>, dim_22 <dbl>,
## #   dim_23 <dbl>, dim_24 <dbl>, dim_25 <dbl>, dim_26 <dbl>, dim_27 <dbl>,
## #   dim_28 <dbl>, dim_29 <dbl>, dim_30 <dbl>, dim_31 <dbl>, dim_32 <dbl>,
## #   dim_33 <dbl>, dim_34 <dbl>, dim_35 <dbl>, dim_36 <dbl>, dim_37 <dbl>,
## #   dim_38 <dbl>, dim_39 <dbl>, dim_40 <dbl>, dim_41 <dbl>, dim_42 <dbl>, ...
```

```
# --- Step 3: Prepare DataFrame for Analysis ---
# Select all columns EXCEPT the first column 'palavra' (word)
# dplyr's select() function is more explicit and safer for this
embeddings_matrix <- data %>%
  select(-palavra)
```

```
print("\nLast rows of the embedding matrix ready for analysis:")
```

```
## [1] "\nLast rows of the embedding matrix ready for analysis:"
```

```
print(tail(embeddings_matrix))
```

```
## # A tibble: 6 x 768
##   dim_1 dim_2 dim_3 dim_4 dim_5 dim_6 dim_7 dim_8 dim_9 dim_10
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1  0.0132 0.139 -0.0165 0.0440 0.0908 0.0228 -0.00486 -0.0215 -0.0283 0.0853
```

```
## 2 -0.0365  0.0471 -0.0175  0.0156  0.0795  0.0494 -0.129   -0.0490   0.00369  0.110
## 3 -0.00446  0.0765 -0.0176  0.0571  0.0892  0.0183   0.00473 -0.00311 -0.0192   0.0863
## 4 -0.00477  0.151   -0.0158  0.0310  0.0590  0.0623 -0.0435   -0.0371   0.00316  0.0854
## 5 -0.0233   0.0185 -0.0179  0.0351  0.0735  0.0101 -0.0373   -0.0110  -0.00532  0.0934
## 6 -0.0211   0.162   -0.0154  0.0256  0.0544  0.0554 -0.0346   -0.0209   0.00552  0.0771
## # i 758 more variables: dim_11 <dbl>, dim_12 <dbl>, dim_13 <dbl>, dim_14 <dbl>,
## #   dim_15 <dbl>, dim_16 <dbl>, dim_17 <dbl>, dim_18 <dbl>, dim_19 <dbl>,
## #   dim_20 <dbl>, dim_21 <dbl>, dim_22 <dbl>, dim_23 <dbl>, dim_24 <dbl>,
## #   dim_25 <dbl>, dim_26 <dbl>, dim_27 <dbl>, dim_28 <dbl>, dim_29 <dbl>,
## #   dim_30 <dbl>, dim_31 <dbl>, dim_32 <dbl>, dim_33 <dbl>, dim_34 <dbl>,
## #   dim_35 <dbl>, dim_36 <dbl>, dim_37 <dbl>, dim_38 <dbl>, dim_39 <dbl>,
## #   dim_40 <dbl>, dim_41 <dbl>, dim_42 <dbl>, dim_43 <dbl>, dim_44 <dbl>, ...
```

```
# --- Step 1: Transpose the Embedding Matrix ---
transposed_matrix <- t(embeddings_matrix)
```

```
# --- Step 2: Assign Word Names as Column Names ---
colnames(transposed_matrix) <- data$palavra
```

```
english_words <- c(
  "Fuck", "Great", "Longing", "Shit", "Good", "Rest", "Delight", "Sad",
  "Alone", "Sadness", "Wonder", "Crazy", "Dancing", "Charming", "Chic",
  "Beautiful", "Peace", "Happy", "Vibe", "Wonderful", "Cry", "Crying",
  "Gentle", "Relax", "Tranquility", "Loves", "Loved", "Love", "Like",
  "Heart", "Remember", "Grace", "Triggers", "Think", "Calm", "Top", "Perfect",
  "Bad", "Liked", "Trash", "Addicted", "Banger", "Hell", "Hit", "Memories"
)
data$palavra <- english_words
colnames(transposed_matrix) <- data$palavra
```

## 2.2 Verify if the matrix is factorable

```
cat("--- STEP 1: Bartlett's Test of Sphericity ---\n")
```

```
## --- STEP 1: Bartlett's Test of Sphericity ---
```

```
cor_matrix <- cor(transposed_matrix, use = "pairwise.complete.obs")
bartlett_test <- cortest.bartlett(cor_matrix, n = nrow(transposed_matrix))
print(bartlett_test)
```

```
## $chisq
## [1] 82501.89
##
## $p.value
## [1] 0
##
## $df
## [1] 990
```

```
cat("\n\n--- STEP 2: Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy ---\n")
```

```
##
##
## --- STEP 2: Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy ---
```

```
kmo_test <- KMO(cor_matrix)
print(kmo_test)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = cor_matrix)
## Overall MSA = 0.96
## MSA for each item =
```

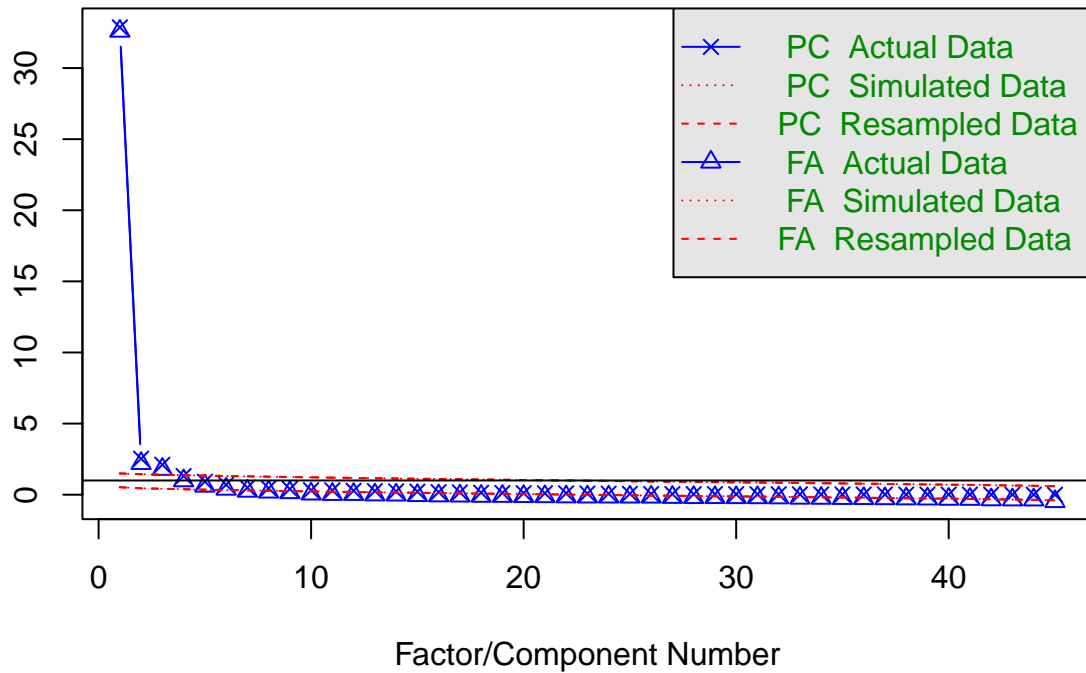
##	Fuck	Great	Longing	Shit	Good	Rest
##	0.96	0.98	0.97	0.95	0.97	0.93
##	Delight	Sad	Alone	Sadness	Wonder	Crazy
##	0.98	0.95	0.98	0.95	0.96	0.99
##	Dancing	Charming	Chic	Beautiful	Peace	Happy
##	0.96	0.92	0.91	0.97	0.94	0.97
##	Vibe	Wonderful	Cry	Crying	Gentle	Relax
##	0.97	0.95	0.96	0.96	0.97	0.95
##	Tranquility	Loves	Loved	Love	Like	Heart
##	0.94	0.93	0.96	0.97	0.93	0.96
##	Remember	Grace	Triggers	Think	Calm	Top
##	0.96	0.96	0.95	0.95	0.95	0.98
##	Perfect	Bad	Liked	Trash	Addicted	Banger
##	0.98	0.97	0.93	0.98	0.98	0.96
##	Hell	Hit	Memories			
##	0.94	0.97	0.94			

## 2.3 Horn's Parallel Analysis for Principal Components and Factor Analysis

```
# --- STEP 1: Run Horn's Parallel Analysis ---
parallel_analysis <- fa.parallel(
  transposed_matrix,
  fa = "both",          # "both" runs the analysis for PCA and Factor Analysis (EFA)
  n.iter = 100,
  show.legend = TRUE,
  main = "Horn's Parallel Analysis"
)
```

eigenvalues of principal components and factor analysis

## Horn's Parallel Analysis



## Parallel analysis suggests that the number of factors = 6 and the number of components = 3

*# Output message analysis:*

*# "Parallel analysis suggests that the number of factors = 6 and the number of components = 3"*

*# --- STEP 2: Prepare data frames for ggplot with English variable names ---*

*# Data frame for the PCA plot*

```
df_plot_pca <- data.frame(
  Number = 1:length(parallel_analysis$pc.values),
  Actual_Eigenvalue = parallel_analysis$pc.values,
  Simulated_Eigenvalue = parallel_analysis$pc.sim
)
```

*# Data frame for the EFA (Exploratory Factor Analysis) plot*

```
df_plot_efa <- data.frame(
  Number = 1:length(parallel_analysis$fa.values),
  Actual_Eigenvalue = parallel_analysis$fa.values,
  Simulated_Eigenvalue = parallel_analysis$fa.sim
)
```

*# --- STEP 3: Create the PCA plot ---*

```
plot_pca <- ggplot(df_plot_pca, aes(x = Number)) +
```

```

geom_line(aes(y = Actual_Eigenvalue, color = "Actual Data (PCA)"), linewidth = 0.7) +
geom_point(aes(y = Actual_Eigenvalue, color = "Actual Data (PCA)", shape = 17, size = 3) +
geom_line(aes(y = Simulated_Eigenvalue, color = "Simulated Data (PCA)"), linetype = "dashed", linewidth

geom_hline(yintercept = 1, linetype = "dotted", color = "black") +

scale_color_manual(
  name = "Analysis",
  values = c("Actual Data (PCA)" = "blue", "Simulated Data (PCA)" = "red")
) +
labs(
  title = "Parallel Analysis (Principal Components)",
  x = "Component Number",
  y = "Eigenvalue"
) +
theme_minimal(base_size = 12) +
theme(legend.position = "top", plot.title = element_text(hjust = 0.5, face = "bold")) +
scale_x_continuous(breaks = seq(0, 45, by = 5))

# --- STEP 4: Create the EFA plot ---
plot_efa <- ggplot(df_plot_efa, aes(x = Number)) +
  geom_line(aes(y = Actual_Eigenvalue, color = "Actual Data (EFA)"), linewidth = 0.7) +
  geom_point(aes(y = Actual_Eigenvalue, color = "Actual Data (EFA)", shape = 17, size = 3) +
  geom_line(aes(y = Simulated_Eigenvalue, color = "Simulated Data (EFA)"), linetype = "dashed", linewidth

  geom_hline(yintercept = 1, linetype = "dotted", color = "black") +

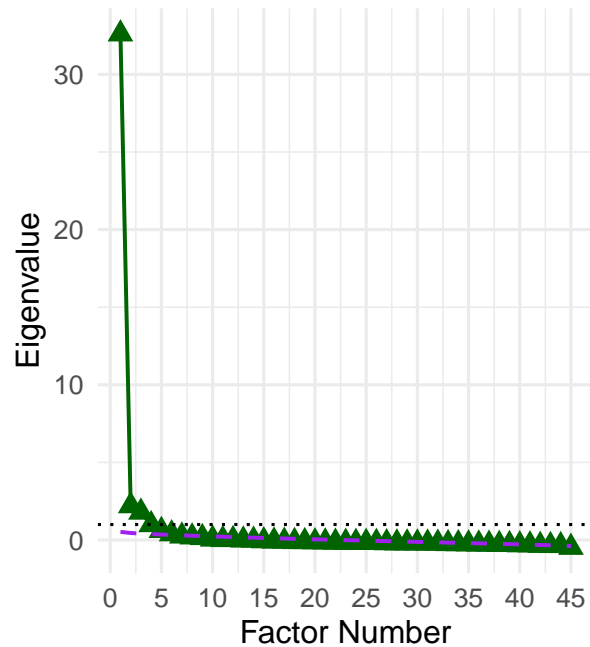
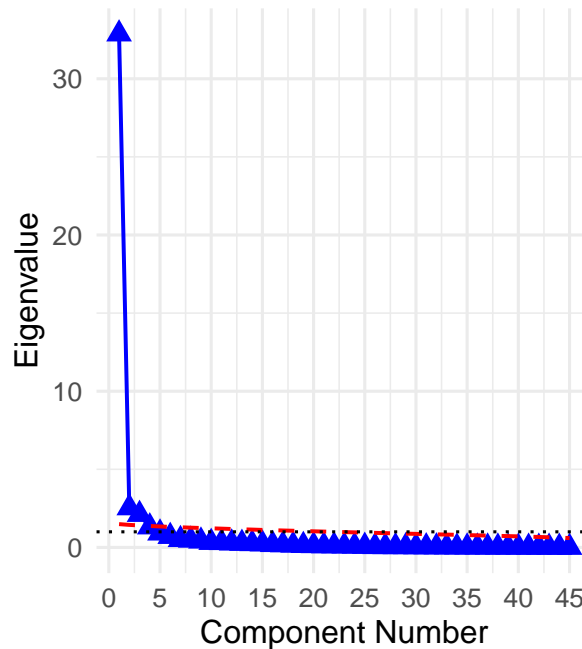
  scale_color_manual(
    name = "Analysis",
    values = c("Actual Data (EFA)" = "darkgreen", "Simulated Data (EFA)" = "purple")
  ) +
  labs(
    title = "Parallel Analysis (Factor Analysis)",
    x = "Factor Number",
    y = "Eigenvalue"
  ) +
  theme_minimal(base_size = 12) +
  theme(legend.position = "top", plot.title = element_text(hjust = 0.5, face = "bold")) +
  scale_x_continuous(breaks = seq(0, 45, by = 5))

# --- STEP 5: Combine both plots side-by-side ---
combined_plot <- plot_pca + plot_efa
print(combined_plot)

```

## Parallel Analysis (Principal Component Analysis) Parallel Analysis (Factor Analysis)

Analysis ▲ Actual Data (PCA) - . Simulated Data (PCA) ▲ Actual Data (EFA) - . Simulated Data (EFA)



```
# Now, save the plot to a file
#ggsave("parallel_analysis.png",width = 12, height = 8, dpi = 300)
```

### 2.4 PCA - General Factor Identification

1st dimension where all words load positively

```
cat("\n--- Running PCA to extract 3 components ---\n")
```

```
##
## --- Running PCA to extract 3 components ---
```

```
pca_results_psych <- principal(
  r = transposed_matrix,
  nfactors = 3,
  rotate = "none" # No rotation to see the raw structure
)
print(pca_results_psych$loadings, cutoff = 0.3, sort = TRUE)
```

```
##
## Loadings:
##          PC1    PC2    PC3
## Fuck      0.816  0.399  0.301
```



```

## Great      0.946
## Longing    0.873
## Shit       0.785  0.351  0.416
## Good       0.925
## Rest       0.767
## Delight    0.869
## Sad        0.865
## Alone      0.840
## Sadness    0.837 -0.387
## Wonder     0.903
## Crazy      0.846  0.413
## Dancing    0.822  0.396
## Charming   0.740  0.425
## Chic       0.721  0.445
## Beautiful  0.912
## Peace      0.854 -0.363
## Happy      0.870
## Vibe       0.932
## Wonderful  0.896
## Cry        0.841
## Crying     0.796
## Gentle     0.887
## Relax      0.790 -0.305
## Tranquility 0.830 -0.376
## Loves      0.886
## Loved      0.896
## Love       0.893
## Like       0.910
## Heart      0.916
## Remember   0.833
## Grace      0.934
## Triggers   0.863
## Think      0.874
## Calm       0.904
## Top        0.817
## Perfect    0.841
## Bad        0.808          0.398
## Liked      0.852
## Trash      0.755  0.333  0.385
## Addicted   0.861
## Banger     0.852          0.307
## Hell       0.798          0.423
## Hit        0.920
## Memories   0.801          0.376
##
##           PC1   PC2   PC3
## SS loadings 32.863 2.532 2.108
## Proportion Var 0.730 0.056 0.047
## Cumulative Var 0.730 0.787 0.833

```

```
pca_results_psych$fit.off
```

```
## [1] 0.9972998
```

```
pc_scores_df <- as.data.frame(pca_results_psych$scores)
```

## 2.5 General factor extraction reveals the circumplex model

```
loadings_df <- as.data.frame(unclass(pca_results_psych$loadings))
loadings_df$palavra <- rownames(loadings_df)

grafico_pca_intensidade_final <- ggplot(
  data = loadings_df,
  aes(x = PC3, y = PC2, label = palavra, size = PC1)
) +

  # Quadrant reference lines
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray50") +
  geom_vline(xintercept = 0, linetype = "dashed", color = "gray50") +

  # Text layer with repulsion
  geom_text_repel(
    fontface = "bold",
    color = "black",
    bg.color = "white",
    bg.r = 0.1,
    segment.color = "transparent",
    max.overlaps = Inf
  ) +

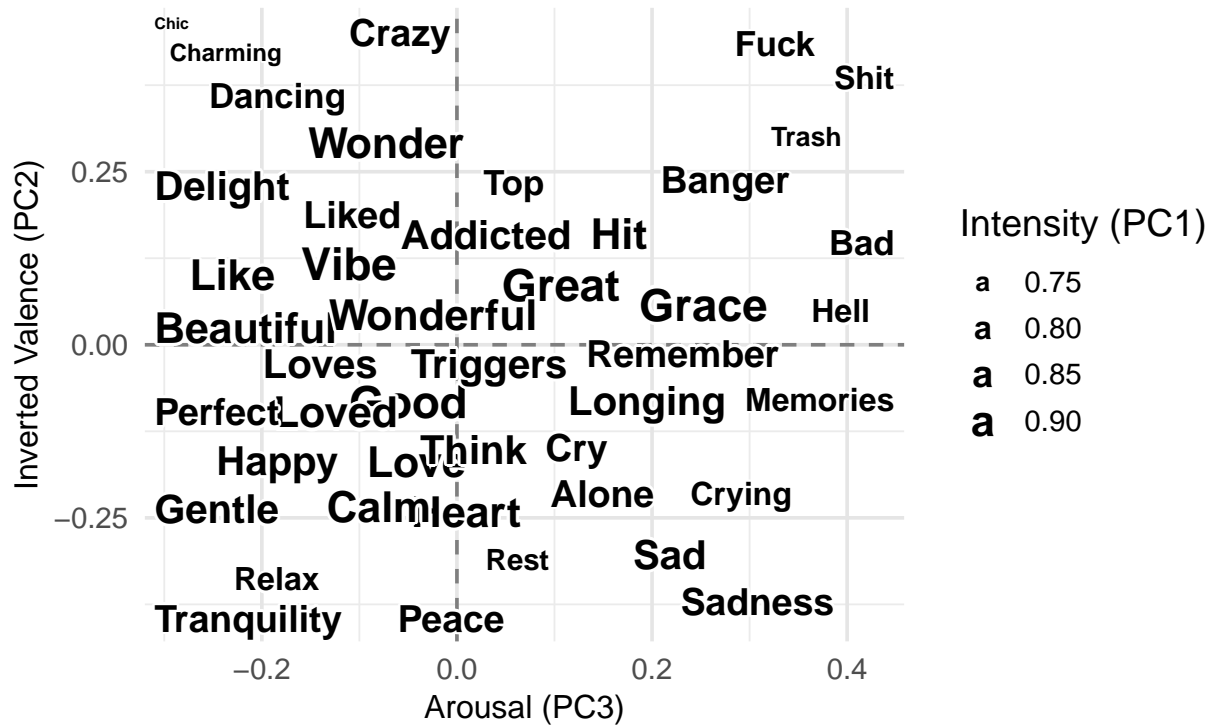
  # Size scale customization
  scale_size_continuous(
    range = c(2, 6),
    name = "Intensity (PC1)"
  ) +
  labs(
    title = "",
    subtitle = "",
    x = "Arousal (PC3)",
    y = "Inverted Valence (PC2)"
  ) +

  # Clean visual theme
  theme_minimal(base_size = 14) +
  theme(
    panel.grid.major = element_line(color = "gray90"),
    plot.title = element_text(hjust = 0.5, face = "bold", size = 18),
    plot.subtitle = element_text(hjust = 0.5, size = 11),
    legend.position = "right",

    axis.title = element_text(size = 12)
  )

# Display final plot
```

```
print(grafico_pca_intensidade_final)
```



```
#ggsave("Figure 2.png",width = 12, height = 8, dpi = 300, bg = "white")
```

## 2.6 PCA with Varimax to better identify words representing PCs

```
cat("\n--- Running PCA to extract 3 components with rotation ---\n")
```

```
##
```

```
## --- Running PCA to extract 3 components with rotation ---
```

```
pca_results_psych <- principal(
  r = transposed_matrix,
  nfactors = 3,
  rotate = "none"
)
#print(pca_results_psych$loadings, cutoff = 0.3, sort = TRUE)
pca_results_psych$fit.off
```

```
## [1] 0.9972998
```

```

# Run PCA with Varimax rotation
pca_results_varimax <- principal(
  r = transposed_matrix,
  nfactors = 3,
  rotate = "varimax"
)

# Extract loadings and convert to dataframe
loadings_df_unique <- as.data.frame(unclass(pca_results_varimax$loadings))

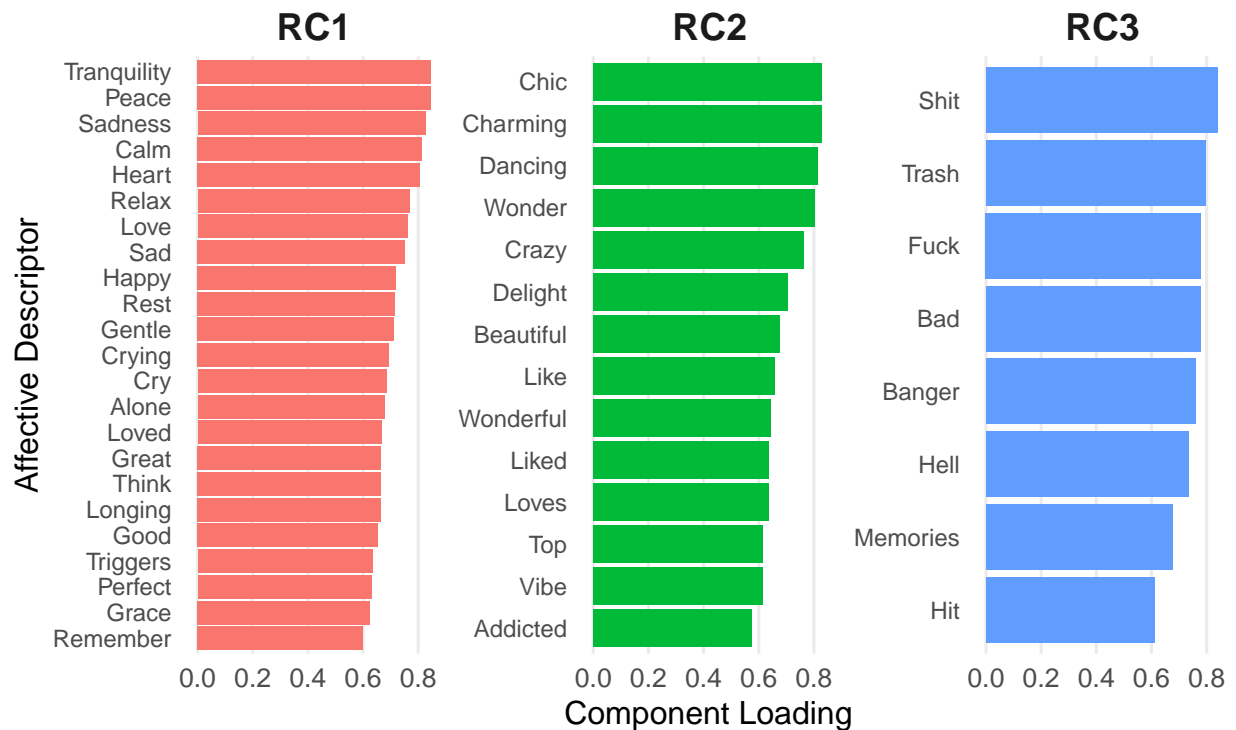
loadings_df_unique <- loadings_df_unique %>%
  mutate(palavra = rownames(.)) %>%
  # Transform to long format
  pivot_longer(
    cols = c("RC1", "RC2", "RC3"),
    names_to = "Component",
    values_to = "Loading"
  ) %>%
  # Group by word
  group_by(palavra) %>%
  filter(abs>Loading) == max(abs>Loading)) %>%
  ungroup() %>%
  # Optional: Filter out low loadings to clean plot
  filter(abs>Loading) > 0.4) %>%
  # Sort words within each component
  group_by(Component) %>%
  mutate(palavra = reorder_within(palavra, Loading, Component))

# Create plot using the unique loadings dataframe
loadings_plot_unique <- ggplot(loadings_df_unique, aes(x = Loading, y = palavra, fill = Component)) +
  geom_col() +
  facet_wrap(~ Component, scales = "free_y") +
  scale_y_reordered() +

  # Aesthetics and Labels
  labs(
    title = "",
    subtitle = "",
    x = "Component Loading",
    y = "Affective Descriptor"
  ) +
  theme_minimal(base_size = 12) +
  theme(
    legend.position = "none",
    strip.text = element_text(face = "bold", size = 14),
    panel.grid.major.y = element_blank(),
    panel.grid.minor.x = element_blank(),
    axis.text.y = element_text(size = 9)
  )

# Display plot
print(loadings_plot_unique)

```



```
# Save in high quality:
#ggsave("Figure 3.png", plot = loadings_plot_unique, bg = "white", width = 12,
#       height = 8, dpi = 300)
```

## 2.7 Formative vs. Reflective

Using PLS-SEM to test if the general factor in this model is formative or reflective

```
# --- PART 1: First-Order Model (to extract scores) ---

# Convert transposed matrix to data frame and clean names
data_df <- as.data.frame(transposed_matrix)
clean_data <- clean_names(data_df)

# Define first-order measurement model
first_order_mm <- constructs(
  composite("HighValence",
    c("remember", "chic", "charming", "dancing", "wonder", "crazy",
      "delight", "beautiful", "like", "wonderful", "liked", "love",
      "top", "vibe"),
    weights = mode_A),

  composite("LowValence",
    c("addicted", "shit", "trash", "fuck", "bad", "banger",
      "hell", "memories", "hit"),
```

```

        weights = mode_A)
)

# Define first-order structural model
first_order_sm <- relationships(
  paths(from = "HighValence", to = "LowValence")
)

# Estimate first-order PLS model
first_order_pls_model <- estimate_pls(
  data = clean_data,
  measurement_model = first_order_mm,
  structural_model = first_order_sm
)

## Generating the seminr model

## All 768 observations are valid.

# Extract scores
construct_scores <- first_order_pls_model$construct_scores
data_with_scores <- cbind(as.data.frame(clean_data), construct_scores)

```

## 2.8 Formative second-order

To validate a formative construct, it needs to POINT towards something. As we lack an external variable, we use an “anchor construct”. We create a reflective anchor construct with RC1 items.

```

# --- PART 2: Second-Order Formative Model ---

# Define measurement model with second-order construct
full_mm_formative <- constructs(
  composite("HighValence", "HighValence"),
  composite("LowValence", "LowValence"),

  # Second-order FORMATIVE construct
  composite("GeneralFactor",
    c("HighValence", "LowValence"),
    weights = mode_B), # mode_B for formative

  # Anchor construct
  composite("Anchor", c("peace", "calm", "sadness", "love"), weights = mode_A)
)

# Define structural model
final_sm <- relationships(
  paths(from = "GeneralFactor", to = "Anchor")
)

# Estimate formative model
final_pls_formative <- estimate_pls(

```

```

data = data_with_scores,
measurement_model = full_mm_formative,
structural_model = final_sm
)

```

```
## Generating the seminr model
```

```
## All 768 observations are valid.
```

```
# Results Analysis
```

```
summary_final_formative <- summary(final_pls_formative)
print(summary_final_formative$reliability)
```

```
##              alpha rhoC  AVE rhoA
## GeneralFactor 0.920 0.950 0.904 1.000
## Anchor        0.954 0.967 0.879 0.957
##
## Alpha, rhoC, and rhoA should exceed 0.7 while AVE should exceed 0.5
```

```
print(summary_final_formative$validity$vif_items)
```

```
## GeneralFactor :
## HighValence LowValence
##          3.649          3.649
##
## Anchor :
##  peace    calm sadness    love
##  5.034    5.701    4.272    4.434
```

```
# Bootstrapping for weight significance
```

```
boot_results_formative <- bootstrap_model(final_pls_formative, nboot = 5000)
```

```
## Bootstrapping model using seminr...
```

```
## SEMinR Model successfully bootstrapped
```

```
summary_boot_formative <- summary(boot_results_formative)
```

```
# Check p-values:
```

```
print(summary_boot_formative$bootstrapped_weights)
```

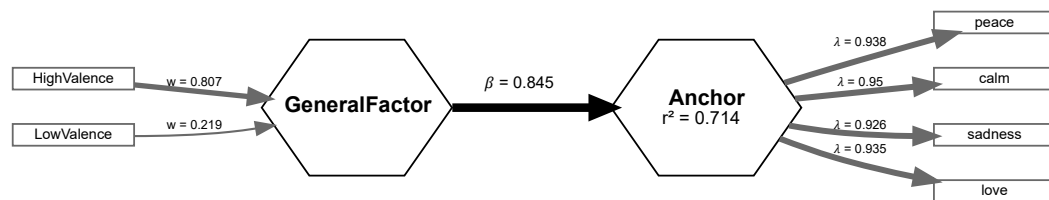
```
##              Original Est. Bootstrap Mean Bootstrap SD
## HighValence -> GeneralFactor      0.807      0.808      0.043
## LowValence  -> GeneralFactor      0.219      0.218      0.047
## peace -> Anchor      0.258      0.258      0.003
## calm  -> Anchor      0.282      0.282      0.004
## sadness -> Anchor      0.246      0.246      0.003
## love  -> Anchor      0.281      0.281      0.003
##
##              T Stat. 2.5% CI 97.5% CI
## HighValence -> GeneralFactor 18.733 0.722 0.891
```

```
## LowValence -> GeneralFactor    4.651    0.126    0.310
## peace -> Anchor                87.386    0.253    0.264
## calm -> Anchor                 67.103    0.274    0.290
## sadness -> Anchor              79.178    0.239    0.252
## love -> Anchor                 83.687    0.275    0.288
```

```
plot(final_pls_formative)
```

```
## file:///C:/Users/vinic/AppData/Local/Temp/Rtmp2p5UKb/file37ec2a015a89/widget37ec577318a0.html screen
```





```
# Extract formative scores
scores_pls_formative <- as.data.frame(final_pls_formative$construct_scores)
```

```

general_factor_formative_scores <- scores_pls_formative$GeneralFactor

if (!require("DiagrammeR")) install.packages("DiagrammeR")

## Carregando pacotes exigidos: DiagrammeR

if (!require("magick")) install.packages("magick")

## Carregando pacotes exigidos: magick

## Warning: pacote 'magick' foi compilado no R versão 4.5.2

## Linking to ImageMagick 6.9.13.29
## Enabled features: cairo, freetype, fftw, ghostscript, heic, lcms, pango, raw, rsvg, webp
## Disabled features: fontconfig, x11

if (!require("DiagrammeRsvg")) install.packages("DiagrammeRsvg")

## Carregando pacotes exigidos: DiagrammeRsvg

plot_formative <- plot(final_pls_formative, title = "")

#temp_svg_file_formative <- tempfile(fileext = ".svg")
#export_svg(plot_formative) %>%
#  charToRaw() %>%
#  writeBin(temp_svg_file_formative)

#image_read_svg(temp_svg_file_formative) %>%
#  image_write(
#    path = "Figure4.png",
#    format = "png",
#    density = 300
#  )

```

## 2.9 Reflective second-order

```

full_mm_reflective <- constructs(
  # First-order constructs
  composite("HighValence", "HighValence"),
  composite("LowValence", "LowValence"),

  # Second-order REFLECTIVE construct
  composite("GeneralFactor",
    c("HighValence", "LowValence"),
    weights = mode_A), # mode_A for reflective

  # Anchor construct
  composite("Anchor", c("peace", "calm", "sadness", "love"), weights = mode_A)

```

```
)

# Structural model
final_sm_reflective <- relationships(
  paths(from = "GeneralFactor", to = "Anchor")
)

# Estimate reflective model
final_pls_reflective <- estimate_pls(
  data = data_with_scores,
  measurement_model = full_mm_reflective,
  structural_model = final_sm_reflective
)
```

```
## Generating the seminr model
```

```
## All 768 observations are valid.
```

```
# Results analysis
summary_final_reflective <- summary(final_pls_reflective)
print(summary_final_reflective$reliability)
```

```
##           alpha rhoC  AVE rhoA
## GeneralFactor 0.920 0.962 0.926 0.926
## Anchor        0.954 0.967 0.879 0.956
##
## Alpha, rhoC, and rhoA should exceed 0.7 while AVE should exceed 0.5
```

```
# Bootstrapping
boot_results_reflective <- bootstrap_model(final_pls_reflective, nboot = 5000)
```

```
## Bootstrapping model using seminr...
```

```
## SEMinR Model successfully bootstrapped
```

```
summary_boot_reflective <- summary(boot_results_reflective)
```

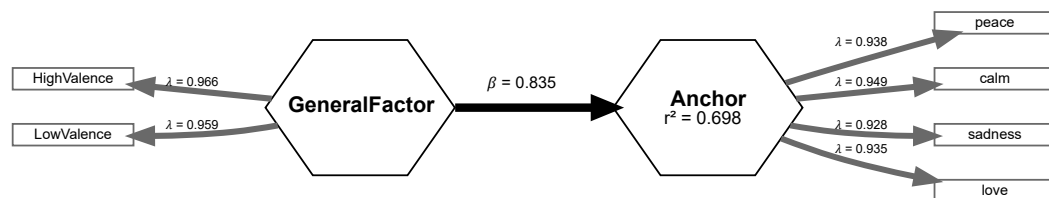
```
# Check p-values for loadings:
print(summary_boot_reflective$bootstrapped_loadings)
```

```
##                                     Original Est. Bootstrap Mean Bootstrap SD
## HighValence -> GeneralFactor      0.966      0.966      0.003
## LowValence  -> GeneralFactor      0.959      0.958      0.005
## peace       -> Anchor              0.938      0.937      0.006
## calm        -> Anchor              0.949      0.949      0.004
## sadness     -> Anchor              0.928      0.927      0.007
## love        -> Anchor              0.935      0.935      0.006
##
##                                     T Stat. 2.5% CI 97.5% CI
## HighValence -> GeneralFactor 311.907  0.959  0.971
## LowValence  -> GeneralFactor 207.084  0.949  0.967
```

```
## peace -> Anchor      154.081  0.925  0.949
## calm  -> Anchor      216.154  0.940  0.957
## sadness -> Anchor    135.129  0.913  0.940
## love  -> Anchor      157.286  0.923  0.946
```

```
plot(final_pls_reflective)
```

```
## file:///C:/Users/vinic/AppData/Local/Temp/Rtmp2p5UKb/file37ec703810d/widget37ec4771310d.html screens
```



```
# Extract scores
scores_pls_reflective <- as.data.frame(final_pls_reflective$construct_scores)
```

```
general_factor_reflective_scores <- scores_pls_reflective$GeneralFactor
```

```
plot_reflexive <- plot(final_pls_reflective)
```

```
# Save plot to temp SVG
#temp_svg_file2 <- tempfile(fileext = ".svg")
#export_svg(plot_reflexive) %>%
# charToRaw() %>%
# writeBin(temp_svg_file2)

# Save as PNG
#image_read_svg(temp_svg_file2) %>%
# image_write("Figure5.png")
```

## 2.10 Reflective via lavaan

Model does not fit even with excellent reliability

```
semantic_model <- '
  HighV    =~ remember + chic + charming + dancing + wonder + crazy +
              delight + beautiful + like + wonderful + liked + love + top + vibe
  LowV     =~ addicted + shit + trash + fuck + bad + hit + hell + memories + banger
  '

fit_semantic <- cfa(semantic_model, data = clean_data, estimator = "MLR", orthogonal = F)
fitmeasures(fit_semantic, c("chisq", "df", "pvalue", "cfi", "rmsea",
                           "rmsea.ci.lower", "rmsea.ci.upper"))
```

```
##          chisq          df          pvalue          cfi          rmsea
##    15568.181      229.000          0.000          0.610          0.295
## rmsea.ci.lower rmsea.ci.upper
##          0.291          0.299
```

```
summary(fit_semantic, fit.measures = TRUE, standardized = TRUE)
```

```
## lavaan 0.6-20 ended normally after 269 iterations
##
##      Estimator              ML
##      Optimization method    NLMINB
##      Number of model parameters    47
##
##      Number of observations      768
##
## Model Test User Model:
##
##              Standard      Scaled
##      Test Statistic    15568.181  12774.108
##      Degrees of freedom      229      229
##      P-value (Chi-square)    0.000      0.000
##      Scaling correction factor      1.219
##      Yuan-Bentler correction (Mplus variant)
##
```

```

## Model Test Baseline Model:
##
##   Test statistic           39589.355   32948.102
##   Degrees of freedom           253       253
##   P-value                     0.000       0.000
##   Scaling correction factor           1.202
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)           0.610       0.616
##   Tucker-Lewis Index (TLI)             0.569       0.576
##
##   Robust Comparative Fit Index (CFI)           0.611
##   Robust Tucker-Lewis Index (TLI)           0.570
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)           36121.193   36121.193
##   Scaling correction factor           1.814
##   for the MLR correction
##   Loglikelihood unrestricted model (H1)       43905.283   43905.283
##   Scaling correction factor           1.320
##   for the MLR correction
##
##   Akaike (AIC)           -72148.385   -72148.385
##   Bayesian (BIC)         -71930.127   -71930.127
##   Sample-size adjusted Bayesian (SABIC)       -72079.373   -72079.373
##
## Root Mean Square Error of Approximation:
##
##   RMSEA           0.295       0.267
##   90 Percent confidence interval - lower       0.291       0.264
##   90 Percent confidence interval - upper       0.299       0.271
##   P-value H_0: RMSEA <= 0.050           0.000       0.000
##   P-value H_0: RMSEA >= 0.080           1.000       1.000
##
##   Robust RMSEA           0.295
##   90 Percent confidence interval - lower       0.291
##   90 Percent confidence interval - upper       0.299
##   P-value H_0: Robust RMSEA <= 0.050           0.000
##   P-value H_0: Robust RMSEA >= 0.080           1.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR           0.080       0.080
##
## Parameter Estimates:
##
##   Standard errors           Sandwich
##   Information bread         Observed
##   Observed information based on           Hessian
##
## Latent Variables:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all

```

```

## HighV =~
## remember      1.000      0.047      0.770
## chic          1.321      0.120     10.973      0.000      0.062      0.831
## charming      1.309      0.114     11.492      0.000      0.061      0.844
## dancing       1.261      0.089     14.178      0.000      0.059      0.904
## wonder        1.281      0.068     18.758      0.000      0.060      0.966
## crazy         1.198      0.081     14.721      0.000      0.056      0.905
## delight       1.221      0.047     26.159      0.000      0.057      0.903
## beautiful     1.341      0.046     29.241      0.000      0.063      0.929
## like          1.153      0.039     29.449      0.000      0.054      0.914
## wonderful     1.347      0.049     27.474      0.000      0.063      0.907
## liked         1.178      0.042     28.227      0.000      0.055      0.867
## love          0.985      0.034     29.385      0.000      0.046      0.805
## top           1.064      0.051     21.024      0.000      0.050      0.829
## vibe          1.215      0.035     34.672      0.000      0.057      0.923
## LowV =~
## addicted      1.000      0.056      0.839
## shit          0.990      0.033     29.892      0.000      0.055      0.959
## trash         0.931      0.035     26.332      0.000      0.052      0.910
## fuck          0.991      0.029     33.974      0.000      0.055      0.963
## bad           0.892      0.028     32.080      0.000      0.050      0.897
## hit           0.878      0.026     34.042      0.000      0.049      0.925
## hell          0.885      0.032     27.739      0.000      0.049      0.818
## memories      0.876      0.034     26.108      0.000      0.049      0.780
## banger        0.947      0.029     33.115      0.000      0.053      0.955
##
## Covariances:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## HighV ~~
## LowV          0.002      0.000      7.721      0.000      0.835      0.835
##
## Variances:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .remember      0.002      0.000     11.587      0.000      0.002      0.406
## .chic           0.002      0.000      4.625      0.000      0.002      0.310
## .charming       0.002      0.000      4.506      0.000      0.002      0.287
## .dancing        0.001      0.000      3.824      0.000      0.001      0.183
## .wonder         0.000      0.000      2.592      0.010      0.000      0.066
## .crazy          0.001      0.000      3.918      0.000      0.001      0.180
## .delight        0.001      0.000      8.357      0.000      0.001      0.184
## .beautiful      0.001      0.000      4.572      0.000      0.001      0.137
## .like           0.001      0.000      6.587      0.000      0.001      0.166
## .wonderful      0.001      0.000      5.042      0.000      0.001      0.177
## .liked          0.001      0.000      8.643      0.000      0.001      0.249
## .love           0.001      0.000     10.789      0.000      0.001      0.351
## .top            0.001      0.000     13.629      0.000      0.001      0.313
## .vibe           0.001      0.000      4.850      0.000      0.001      0.148
## .addicted       0.001      0.000     15.509      0.000      0.001      0.295
## .shit           0.000      0.000     10.746      0.000      0.000      0.080
## .trash          0.001      0.000     13.254      0.000      0.001      0.172
## .fuck           0.000      0.000      9.699      0.000      0.000      0.073
## .bad            0.001      0.000     15.535      0.000      0.001      0.195
## .hit            0.000      0.000     12.757      0.000      0.000      0.144
## .hell           0.001      0.000     14.883      0.000      0.001      0.330

```



```
##      .memories      0.002    0.000   15.315    0.000    0.002    0.392
##      .banger        0.000    0.000   11.808    0.000    0.000    0.087
##      HighV          0.002    0.000    7.826    0.000    1.000    1.000
##      LowV           0.003    0.000    9.473    0.000    1.000    1.000
```

```
semTools::compRelSEM(fit_semantic)
```

```
## HighV LowV
## 0.982 0.964
```

## 2.11 Study 1 Correlations

```
## GENERAL FACTOR
matriz <- cbind(scores_pls_reflective[1], scores_pls_formative[1], pca_results_psych$scores[,1])
colnames(matriz) <- c("GF_Reflective", "GF_Formative", "PC1")
#mvn(matriz, univariateTest = "SW")
corCi(matriz, method = "spearman", plot = F)
```

```
## Call:corCi(x = matriz, method = "spearman", plot = F)
##
## Coefficients and bootstrapped confidence intervals
##           GF_Rf GF_Fr PC1
## GF_Reflective 1.00
## GF_Formative  0.99  1.00
## PC1           0.97  0.97  1.00
##
## scale correlations and bootstrapped confidence intervals
##           lower.emp lower.norm estimate upper.norm upper.emp p
## GF_Rf-GF_Fr    0.98    0.98    0.99    0.99    0.99 0
## GF_Rf-PC1      0.96    0.96    0.97    0.97    0.97 0
## GF_Fr-PC1      0.97    0.97    0.97    0.98    0.97 0
```

```
# SPECIFIC FACTORS
especificos <- as.data.frame(construct_scores)
matriz_especificos <- cbind(especificos, pc_scores_df[2:3])
#mvn(matriz_especificos, univariateTest = "SW")
corCi(matriz_especificos, method = "spearman", plot = F)
```

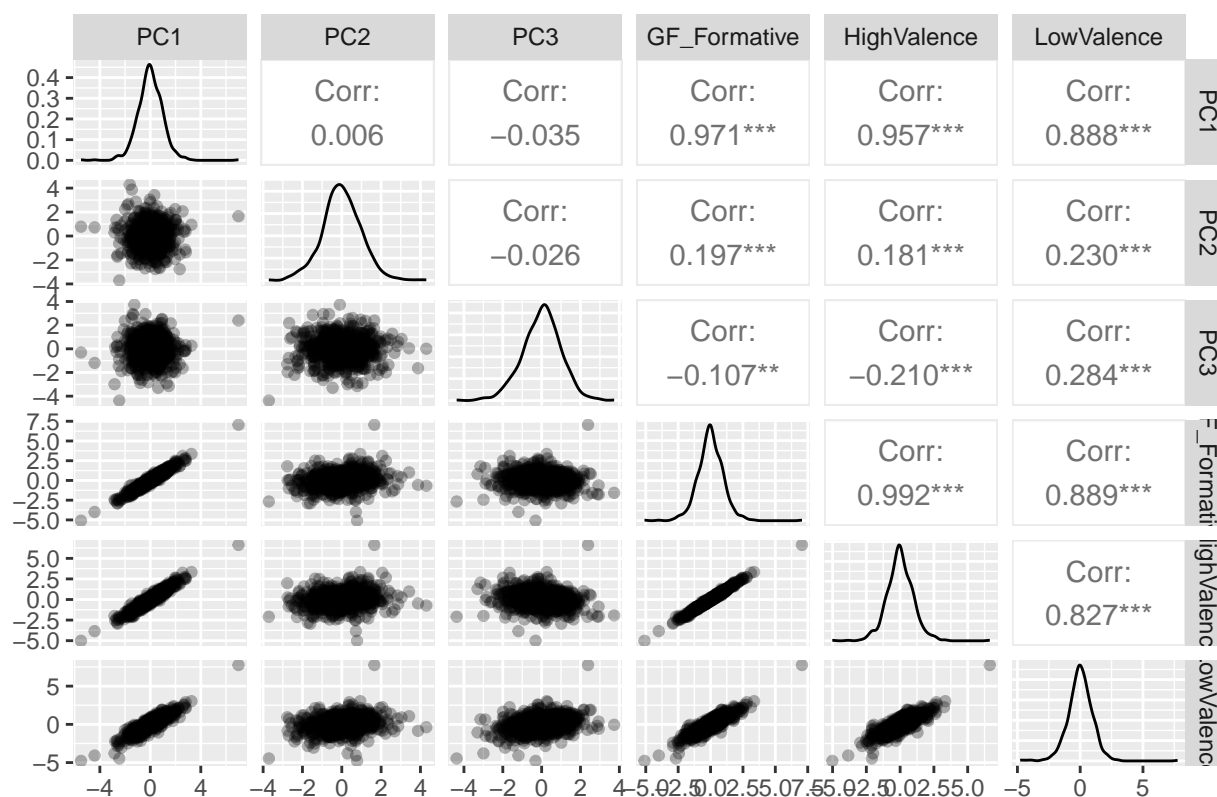
```
## Call:corCi(x = matriz_especificos, method = "spearman", plot = F)
##
## Coefficients and bootstrapped confidence intervals
##           HghVl LwVln PC2  PC3
## HighValence  1.00
## LowValence   0.83  1.00
## PC2          0.18  0.23  1.00
## PC3         -0.21  0.28 -0.03  1.00
##
## scale correlations and bootstrapped confidence intervals
##           lower.emp lower.norm estimate upper.norm upper.emp p
## HghVl-LwVln    0.80    0.80    0.83    0.85    0.85 0.00
```

## HghV1-PC2	0.11	0.10	0.18	0.25	0.25	0.00
## HghV1-PC3	-0.27	-0.27	-0.21	-0.15	-0.15	0.00
## LwVln-PC2	0.16	0.15	0.23	0.30	0.30	0.00
## LwVln-PC3	0.22	0.22	0.28	0.35	0.36	0.00
## PC2-PC3	-0.09	-0.10	-0.03	0.04	0.03	0.39

```
pc_scores_df <- as.data.frame(pca_results_psych$scores)

# Create dataframe for convergence analysis
convergence_study1_df <- data.frame(
  PC1 = pc_scores_df$PC1,
  PC2 = pc_scores_df$PC2,
  PC3 = pc_scores_df$PC3,
  GF_Formative = general_factor_formative_scores,
  HighValence = especificos$HighValence,
  LowValence = especificos$LowValence
)

# GGpairs visualization
cor_plot <- GGally::ggpairs(
  convergence_study1_df,
  title = "",
  upper = list(continuous = wrap("cor", method = "spearman", size = 4)),
  lower = list(continuous = wrap("points", alpha = 0.3))
)
print(cor_plot)
```



```
#ggsave("Figure6.png", plot = cor_plot, bg = "white", width = 10,
#       height = 6, dpi = 300)
```

### 3 Estimates with PANAS

```
load("data.RData")
panas_data <- as.data.frame(data[97:116])
str(panas_data)
```

```
## 'data.frame':   457 obs. of  20 variables:
## $ PN1ativo : num  5 4 4 5 4 4 4 2 5 4 ...
## $ PN2envergo : num  1 1 4 3 2 2 2 1 2 2 ...
## $ PN3atento : num  4 4 4 4 4 3 4 4 4 3 ...
## $ PN4aflit : num  2 5 3 4 5 3 2 2 2 4 ...
## $ PN5determ : num  4 3 4 4 4 4 4 3 5 4 ...
## $ PN6culpado : num  1 4 4 2 2 3 2 1 2 2 ...
## $ PN7empol : num  2 2 4 2 4 3 4 3 5 5 ...
## $ PN8irrit : num  1 4 2 5 4 3 2 1 3 4 ...
## $ PN9interes : num  5 2 4 1 5 4 4 3 5 5 ...
## $ PN10medo : num  1 4 1 5 4 1 3 2 2 4 ...
## $ PN11orgul : num  4 1 5 1 2 4 3 4 5 4 ...
## $ PN12hostil : num  1 4 4 5 1 3 3 1 2 2 ...
```

```
## $ PN13alerta : num 4 4 4 5 3 4 3 1 5 3 ...
## $ PN14inque : num 4 4 3 5 4 4 3 2 3 3 ...
## $ PN15entusia: num 4 1 4 1 4 4 4 3 5 4 ...
## $ PN16nervo : num 1 4 3 5 4 4 2 1 3 4 ...
## $ PN17forte : num 4 1 5 1 5 3 3 4 5 4 ...
## $ PN18apavo : num 1 4 4 3 3 1 2 1 2 2 ...
## $ PN19inspi : num 4 1 5 1 5 3 4 5 5 4 ...
## $ PN20chate : num 1 4 4 5 2 4 2 1 2 2 ...
```

### 3.1 Factorability

```
cat("--- Bartlett's Test of Sphericity ---\n")
```

```
## --- Bartlett's Test of Sphericity ---
```

```
poly <- polychoric(panas_data)
cor_poly <- poly$rho
bartlett_results_correto <- cortest.bartlett(cor_poly)
```

```
## Warning in cortest.bartlett(cor_poly): n not specified, 100 used
```

```
print(bartlett_results_correto)
```

```
## $chisq
## [1] 1179.216
##
## $p.value
## [1] 2.56106e-142
##
## $df
## [1] 190
```

```
cat("\n--- Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy ---\n")
```

```
##
## --- Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy ---
```

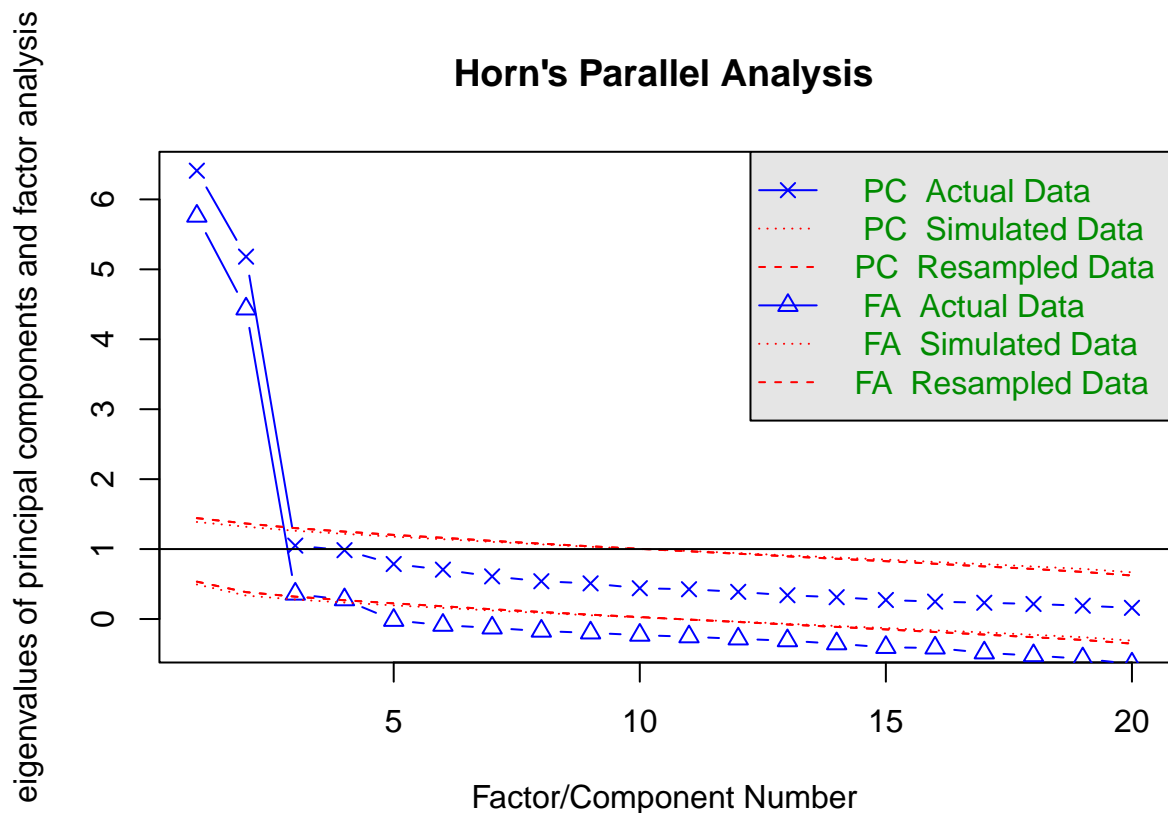
```
kmo_results_correto <- KMO(cor_poly)
print(kmo_results_correto)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = cor_poly)
## Overall MSA = 0.89
## MSA for each item =
##      PN1ativo  PN2envergo  PN3atento  PN4aflit  PN5determ  PN6culpado
##          0.89          0.91          0.86          0.87          0.92          0.87
##      PN7empol  PN8irrit  PN9interes  PN10medo  PN11orgul  PN12hostil
##          0.91          0.89          0.91          0.90          0.93          0.85
##      PN13alerta  PN14inque  PN15entusia  PN16nervo  PN17forte  PN18apavo
##          0.82          0.88          0.91          0.85          0.91          0.89
##      PN19inspi  PN20chate
##          0.89          0.91
```

### 3.2 Horn's Parallel Analysis

```
parallel_analysis_results <- fa.parallel(
  panas_data,
  fa = "both",
  n.iter = 100,
  show.legend = TRUE,
  cor="poly",
  main = "Horn's Parallel Analysis"
)
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs = np.obs, :
## The estimated weights for the factor scores are probably incorrect. Try a
## different factor score estimation method.
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs = np.obs, :
## The estimated weights for the factor scores are probably incorrect. Try a
## different factor score estimation method.
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs = np.obs, :
## The estimated weights for the factor scores are probably incorrect. Try a
## different factor score estimation method.
```



```
## Parallel analysis suggests that the number of factors = 4 and the number of components = 2
```

### 3.3 Parallel Analysis Plot

```
# --- STEP 1: Prepare data frames for plotting ---

# Data frame for PCA plot
df_plot_pca <- data.frame(
  Number = 1:length(parallel_analysis_results$pc.values),
  Actual_Eigenvalue = parallel_analysis_results$pc.values,
  Simulated_Eigenvalue = parallel_analysis_results$pc.sim
)

# Data frame for EFA plot
df_plot_efa <- data.frame(
  Number = 1:length(parallel_analysis_results$fa.values),
  Actual_Eigenvalue = parallel_analysis_results$fa.values,
  Simulated_Eigenvalue = parallel_analysis_results$fa.sim
)

# --- STEP 2: Create PCA plot ---
plot_pca <- ggplot(df_plot_pca, aes(x = Number)) +
  geom_line(aes(y = Actual_Eigenvalue, color = "Actual Data (PCA)"), linewidth = 0.7) +
  geom_point(aes(y = Actual_Eigenvalue, color = "Actual Data (PCA)"), shape = 17, size = 3) +
  geom_line(aes(y = Simulated_Eigenvalue, color = "Simulated Data (PCA)"), linetype = "dashed", linewidth = 0.7) +
  geom_hline(yintercept = 1, linetype = "dotted", color = "black") +
  scale_color_manual(
    name = "Analysis",
    values = c("Actual Data (PCA)" = "blue", "Simulated Data (PCA)" = "red")
  ) +
  labs(
    title = "Parallel Analysis (Principal Components)",
    x = "Component Number",
    y = "Eigenvalue"
  ) +
  theme_minimal(base_size = 12) +
  theme(legend.position = "top", plot.title = element_text(hjust = 0.5, face = "bold")) +
  scale_x_continuous(breaks = seq(0, 45, by = 5))

# --- STEP 3: Create EFA plot ---
plot_efa <- ggplot(df_plot_efa, aes(x = Number)) +
  geom_line(aes(y = Actual_Eigenvalue, color = "Actual Data (EFA)"), linewidth = 0.7) +
  geom_point(aes(y = Actual_Eigenvalue, color = "Actual Data (EFA)"), shape = 17, size = 3) +
  geom_line(aes(y = Simulated_Eigenvalue, color = "Simulated Data (EFA)"), linetype = "dashed", linewidth = 0.7) +
  geom_hline(yintercept = 1, linetype = "dotted", color = "black") +
  scale_color_manual(
    name = "Analysis",
    values = c("Actual Data (EFA)" = "darkgreen", "Simulated Data (EFA)" = "purple")
  ) +
```

```

labs(
  title = "Parallel Analysis (Factor Analysis)",
  x = "Factor Number",
  y = "Eigenvalue"
) +
theme_minimal(base_size = 12) +
theme(legend.position = "top", plot.title = element_text(hjust = 0.5, face = "bold")) +
scale_x_continuous(breaks = seq(0, 45, by = 5))

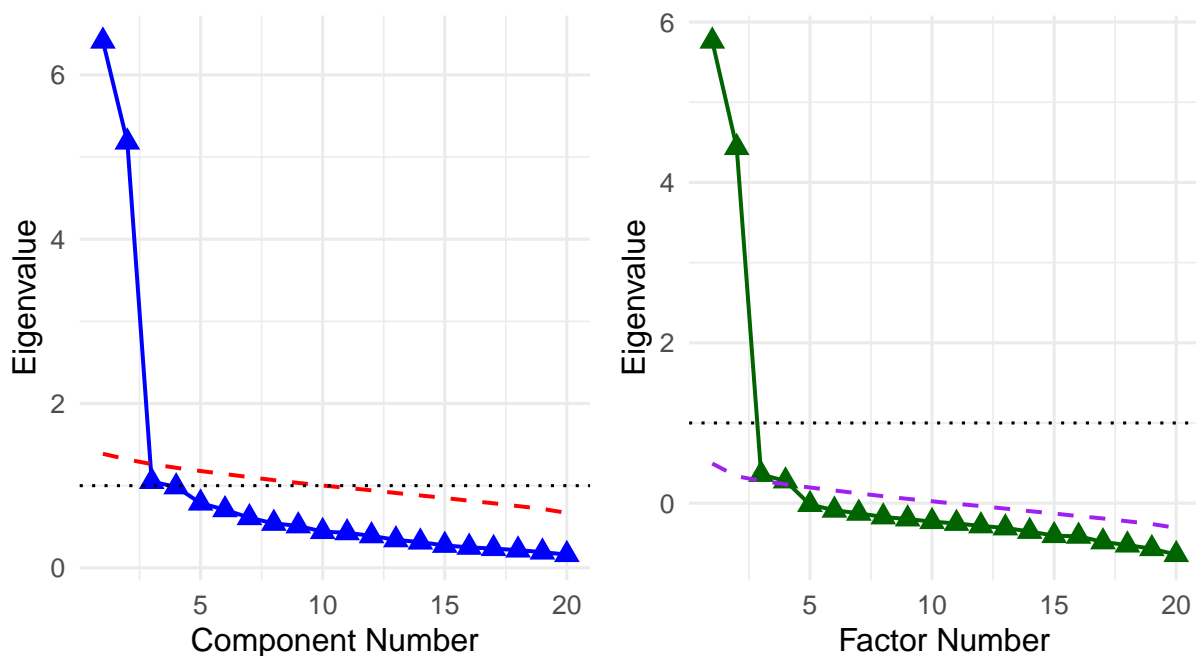
# --- STEP 4: Combine plots ---
combined_plot <- plot_pca + plot_efa

print(combined_plot)

```

## Parallel Analysis (Principal Component Analysis) Parallel Analysis (Factor Analysis)

Actual Data (PCA) Simulated Data (PCA) Actual Data (EFA) Simulated Data (EFA)



```

ggsave("Figure7.png", plot = combined_plot, width = 12, height = 5, dpi = 300,
  bg = "white")

```

### 3.4 PANAS PCA

The first component represents valence, while the second represents Intensity/Salience, with all words loading positively.

```

library(dplyr)

# Standard PANAS items (Watson et al., 1988)
panas_english_names <- c(
  "PN1ativo"      = "Active",
  "PN2envergo"    = "Ashamed",
  "PN3atento"     = "Attentive",
  "PN4aflit"      = "Distressed",
  "PN5determ"     = "Determined",
  "PN6culpado"    = "Guilty",
  "PN7empol"      = "Excited",
  "PN8irrit"      = "Irritable",
  "PN9interes"    = "Interested",
  "PN10medo"      = "Scared",
  "PN11orgul"     = "Proud",
  "PN12hostil"    = "Hostile",
  "PN13alerta"    = "Alert",
  "PN14inquinie"  = "Jittery",
  "PN15entusia"   = "Enthusiastic",
  "PN16nervo"     = "Nervous",
  "PN17forte"     = "Strong",
  "PN18apavo"     = "Afraid",
  "PN19inspi"     = "Inspired",
  "PN20chate"     = "Upset"
)

panas_data <- panas_data %>%
  rename(any_of(setNames(names(panas_english_names), panas_english_names)))

# Run PCA with English names
pca_results_psych <- principal(
  r = panas_data,
  nfactors = 2,
  rotate = "none"
)

# Print loadings
print(pca_results_psych$loadings, cutoff = 0.30, sort = TRUE)

```

```

##
## Loadings:
##      PC1    PC2
## Active    0.637 0.363
## Attentive  0.592 0.405
## Determined 0.653 0.415
## Guilty    -0.503 0.474
## Excited    0.695 0.384
## Interested 0.596 0.494
## Proud      0.668 0.380
## Enthusiastic 0.692 0.426
## Strong     0.574 0.432
## Afraid    -0.580 0.407

```



```
## Inspired      0.610  0.378
## Distressed   -0.527  0.570
## Irritable    -0.366  0.619
## Scared       -0.496  0.590
## Alert        0.560
## Jittery     -0.373  0.599
## Nervous      -0.457  0.699
## Upset        -0.540  0.550
## Ashamed      -0.345  0.412
## Hostile      -0.325  0.482
##
##              PC1    PC2
## SS loadings   5.791  4.826
## Proportion Var 0.290  0.241
## Cumulative Var 0.290  0.531
```

```
cat("\n--- Running PCA to extract 2 components ---\n")
```

```
##
## --- Running PCA to extract 2 components ---
```

```
pca_results_psych <- principal(
  r = panas_data,
  nfactors = 2,
  rotate = "none"
)

print(pca_results_psych$loadings, cutoff = 0.30, sort = TRUE)
```

```
##
## Loadings:
##              PC1    PC2
## Active       0.637  0.363
## Attentive    0.592  0.405
## Determined   0.653  0.415
## Guilty       -0.503  0.474
## Excited      0.695  0.384
## Interested   0.596  0.494
## Proud        0.668  0.380
## Enthusiastic 0.692  0.426
## Strong       0.574  0.432
## Afraid       -0.580  0.407
## Inspired     0.610  0.378
## Distressed   -0.527  0.570
## Irritable    -0.366  0.619
## Scared       -0.496  0.590
## Alert        0.560
## Jittery     -0.373  0.599
## Nervous      -0.457  0.699
## Upset        -0.540  0.550
## Ashamed      -0.345  0.412
## Hostile      -0.325  0.482
##
```

```
##           PC1   PC2
## SS loadings  5.791 4.826
## Proportion Var 0.290 0.241
## Cumulative Var 0.290 0.531
```

```
pca_results_psych$fit.off
```

```
## [1] 0.9696769
```

### 3.5 Plot

```
# Prepare dataframe for plot
loadings_df <- as.data.frame(unclass(pca_results_psych$loadings))
loadings_df$palavra <- rownames(loadings_df)

grafico_panas_2D_simples <- ggplot(
  data = loadings_df,
  aes(x = PC1, y = PC2, label = palavra)
) +

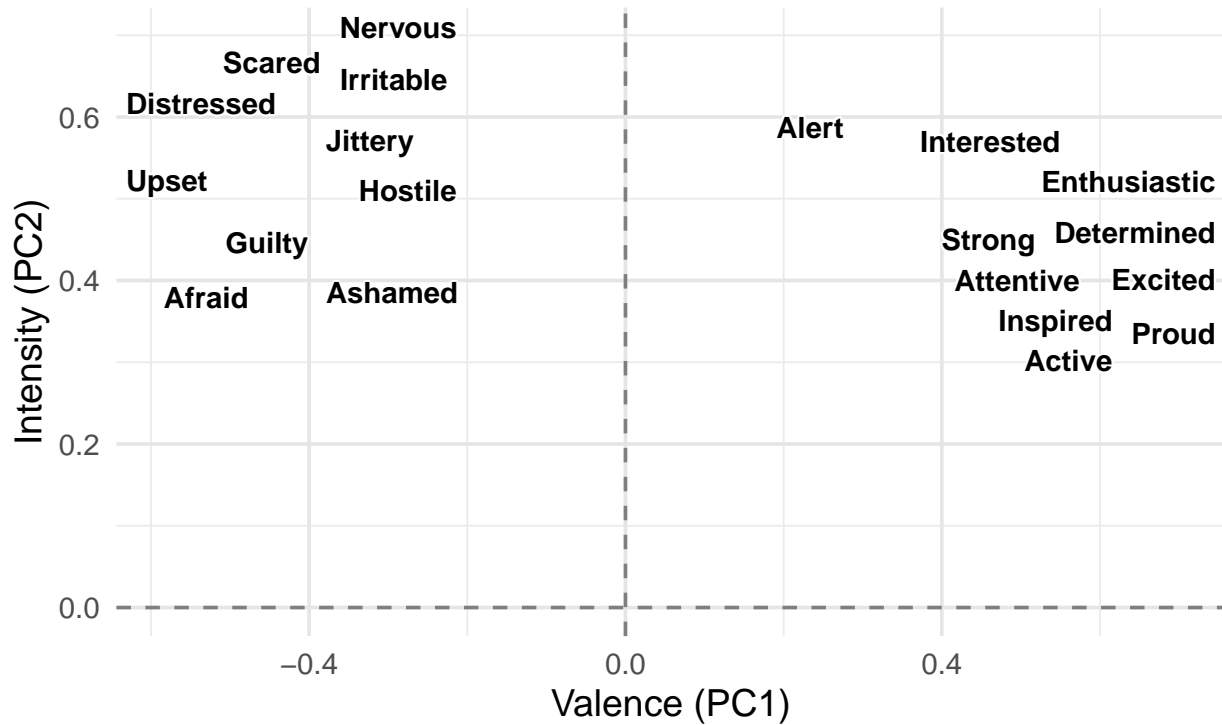
# Reference lines
geom_hline(yintercept = 0, linetype = "dashed", color = "gray50") +
geom_vline(xintercept = 0, linetype = "dashed", color = "gray50") +

# Text layer
geom_text_repel(
  fontface = "bold",
  color = "black",
  bg.color = "white",
  bg.r = 0.1,
  segment.color = "transparent",
  max.overlaps = Inf,
  size = 4
) +

labs(
  title = "",
  subtitle = "",
  x = "Valence (PC1)",
  y = "Intensity (PC2)"
) +

theme_minimal(base_size = 14) +
theme(
  panel.grid.major = element_line(color = "gray90"),
  plot.title = element_text(hjust = 0.5, face = "bold", size = 18),
  plot.subtitle = element_text(hjust = 0.5, size = 11),
  legend.position = "none"
)
```

```
# Display final plot
print(grafico_panas_2D_simples)
```



```
#ggsave("mapaPANAS.png", plot = grafico_panas_2D_simples,
#       width = 12, height = 6, units = "in", dpi = 300, bg = "white")
```

### 3.6 With rotation to extract components

```
cat("\n--- Running PCA to extract 2 components with Varimax ---\n")
```

```
##
## --- Running PCA to extract 2 components with Varimax ---
```

```
pca_results_psych <- principal(
  r = panas_data,
  nfactors = 2,
  rotate = "varimax"
)
```

```
pca_results_psych$fit.off
```

```
## [1] 0.9696769
```

```

# Extract loadings
loadings_df_unique <- as.data.frame(unclass(pca_results_psych$loadings))

loadings_df_unique <- loadings_df_unique %>%
  mutate(palavra = rownames(.)) %>%
  pivot_longer(
    cols = c("RC1", "RC2"),
    names_to = "Component",
    values_to = "Loading"
  ) %>%
  group_by(palavra) %>%
  # Filter to keep highest absolute loading
  filter(abs>Loading) == max(abs>Loading)) %>%
  ungroup() %>%
  filter(abs>Loading) > 0.4) %>%
  group_by(Component) %>%
  mutate(palavra = reorder_within(palavra, Loading, Component))

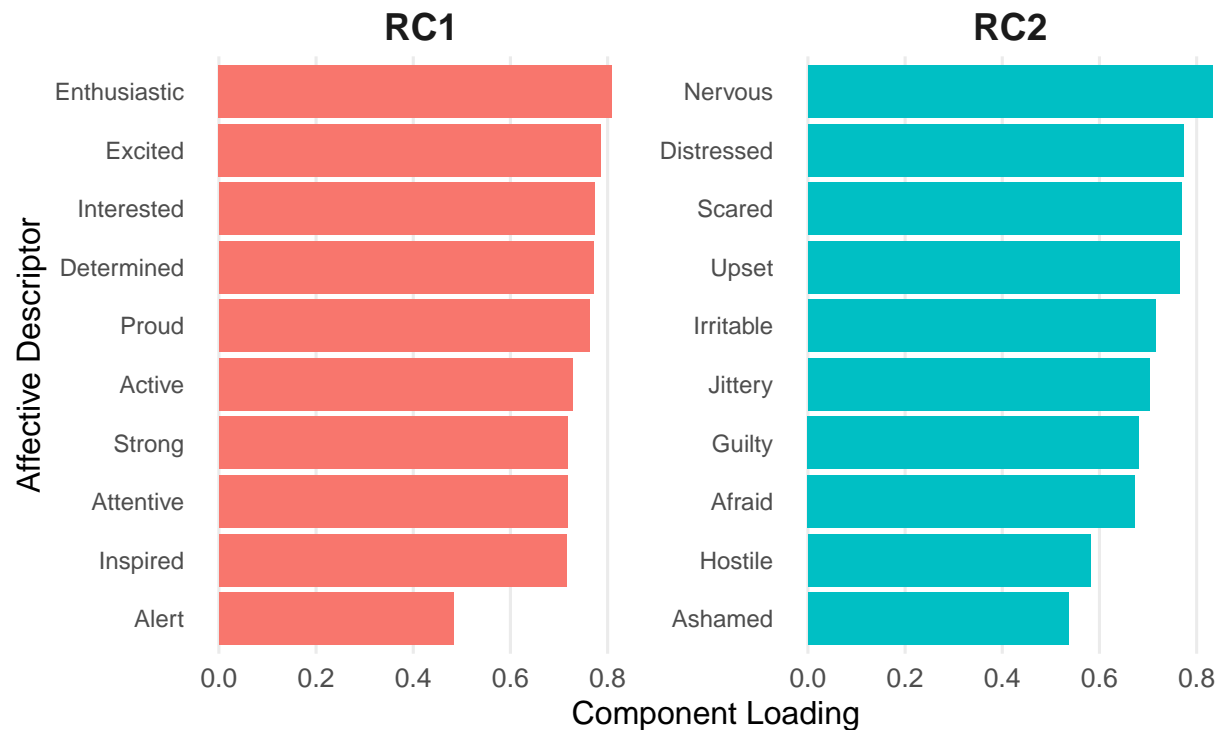
# Create plot
loadings_plot_unique <- ggplot(loadings_df_unique, aes(x = Loading, y = palavra, fill = Component)) +
  geom_col() +
  facet_wrap(~ Component, scales = "free_y") +
  scale_y_reordered() +

# Aesthetics
labs(
  title = "Grouping of Affective Descriptors by Principal Component (Varimax)",
  subtitle = "Each descriptor is assigned to the component with the highest loading",
  x = "Component Loading",
  y = "Affective Descriptor"
) +
theme_minimal(base_size = 12) +
theme(
  legend.position = "none",
  strip.text = element_text(face = "bold", size = 14),
  panel.grid.major.y = element_blank(),
  panel.grid.minor.x = element_blank(),
  axis.text.y = element_text(size = 9)
)

# Display plot
print(loadings_plot_unique)

```

Grouping of Affective Descriptors by Principal Component (Varir  
Each descriptor is assigned to the component with the highest loading



### 3.7 Formative vs. Reflective - PANAS

```
# 1. Define first-order measurement model (PA and NA)
# --- PART 1: First-Order PLS Model for PANAS ---

first_order_mm_panas <- constructs(
  composite("PA", c("Active", "Attentive", "Determined", "Excited",
                    "Interested", "Proud", "Alert", "Enthusiastic",
                    "Strong", "Inspired"),
    weights = mode_A),

  composite("NA", c("Ashamed", "Distressed", "Guilty", "Irritable",
                    "Scared", "Hostile", "Jittery", "Nervous",
                    "Afraid", "Upset"),
    weights = mode_A)
)

# 2. Structural model
first_order_sm_panas <- relationships(
  paths(from = "PA", to = "NA")
)

# 3. Estimate model
first_order_pls_panas <- estimate_pls(
```

```

data = panas_data,
measurement_model = first_order_mm_panas,
structural_model = first_order_sm_panas
)

```

```
## Generating the semnr model
```

```
## All 457 observations are valid.
```

```
summary(first_order_pls_panas)
```

```

##
## Results from package semnr (2.3.7)
##
## Path Coefficients:
##           NA
## R^2      0.068
## AdjR^2   0.066
## PA      -0.261
##
## Reliability:
##   alpha rhoC  AVE rhoA
## PA 0.901 0.894 0.477 0.787
## NA 0.888 0.906 0.494 0.933
##
## Alpha, rhoC, and rhoA should exceed 0.7 while AVE should exceed 0.5

```

```

# 4. Extract scores
panas_scores <- first_order_pls_panas$construct_scores
panas_with_scores <- as.data.frame(cbind(panas_data, panas_scores))

```

### 3.8 Formative - PANAS

```

# --- PART 2: Second-Order Formative Model for PANAS ---

second_order_mm_formative <- constructs(
  composite("PA", "PA"),
  composite("NA", "NA"),

  # Define anchor construct
  composite("Activation_Anchor", c("Excited", "Enthusiastic", "Irritable", "Nervous"), weights = mode_A),

  # Second-order FORMATIVE construct
  composite("G_Factor_Formative", c("PA", "NA"), weights = mode_B)
)

# Structural model
second_order_sm_panas <- relationships(
  paths(from = "G_Factor_Formative", to = "Activation_Anchor")
)

```

```

# Estimate model
pls_panas_formative <- estimate_pls(
  data = panas_with_scores,
  measurement_model = second_order_mm_formative,
  structural_model = second_order_sm_panas
)

## Generating the seminr model

## All 457 observations are valid.

# Analyze VIF
summary_panas_formative <- summary(pls_panas_formative)
print(summary_panas_formative$validity$vif_items)

```

```

## G_Factor_Formative :
##      PA      NA
## 1.073 1.073
##
## Activation_Anchor :
##      Excited Enthusiastic      Irritable      Nervous
##      1.880      1.872      1.623      1.632

```

```

# Bootstrap
boot_panas_formative <- bootstrap_model(pls_panas_formative, nboot = 5000)

```

```
## Bootstrapping model using seminr...
```

```
## SEMinR Model successfully bootstrapped
```

```
summary(boot_panas_formative)$bootstrapped_weights
```

```

##                                Original Est. Bootstrap Mean Bootstrap SD
## Excited -> Activation_Anchor          0.539          0.524          0.035
## Enthusiastic -> Activation_Anchor      0.512          0.499          0.034
## Irritable -> Activation_Anchor        -0.091         -0.076          0.111
## Nervous -> Activation_Anchor          -0.153         -0.134          0.125
## PA -> G_Factor_Formative              0.954          0.935          0.076
## NA -> G_Factor_Formative             -0.141         -0.116          0.210
##
##                                T Stat. 2.5% CI 97.5% CI
## Excited -> Activation_Anchor        15.469    0.447    0.570
## Enthusiastic -> Activation_Anchor    14.996    0.422    0.540
## Irritable -> Activation_Anchor       -0.822   -0.247    0.166
## Nervous -> Activation_Anchor        -1.226   -0.321    0.150
## PA -> G_Factor_Formative            12.584    0.765    1.026
## NA -> G_Factor_Formative            -0.671   -0.450    0.348

```

```
##Reflective - PANAS
```

```
# --- PART 3: Second-Order Reflective Model for PANAS ---

second_order_mm_reflective <- constructs(
  composite("PA", "PA"),
  composite("NA", "NA"),

  composite("Activation_Anchor", c("Excited", "Enthusiastic", "Irritable", "Nervous"), weights = mode_A)

  # Second-order REFLECTIVE construct
  composite("G_Factor_Reflective", c("PA", "NA"), weights = mode_A)
)

# Structural model
second_order_sm_panas_reflective <- relationships(
  paths(from = "G_Factor_Reflective", to = "Activation_Anchor")
)

# Estimate model
pls_panas_reflective <- estimate_pls(
  data = panas_with_scores,
  measurement_model = second_order_mm_reflective,
  structural_model = second_order_sm_panas_reflective
)
```

```
## Generating the seminr model
```

```
## All 457 observations are valid.
```

```
# Reliability
summary_panas_reflective <- summary(pls_panas_reflective)
print(summary_panas_reflective$reliability)
```

```
##              alpha rhoC  AVE rhoA
## G_Factor_Reflective -0.706 0.029 0.626 0.441
## Activation_Anchor    0.486 0.114 0.433 0.596
##
## Alpha, rhoC, and rhoA should exceed 0.7 while AVE should exceed 0.5
```

```
# Bootstrap
boot_panas_reflective <- bootstrap_model(pls_panas_reflective, nboot = 5000)
```

```
## Bootstrapping model using seminr...
```

```
## SEMinR Model successfully bootstrapped
```

```
summary(boot_panas_reflective)$bootstrapped_loadings
```

```
##              Original Est. Bootstrap Mean Bootstrap SD
## Excited -> Activation_Anchor          0.791          0.797          0.045
## Enthusiastic -> Activation_Anchor      0.766          0.772          0.050
```



## Irritable -> Activation_Anchor	-0.484	-0.467	0.110
## Nervous -> Activation_Anchor	-0.533	-0.515	0.107
## PA -> G_Factor_Reflective	0.863	0.869	0.044
## NA -> G_Factor_Reflective	-0.713	-0.698	0.090
##	T Stat.	2.5% CI	97.5% CI
## Excited -> Activation_Anchor	17.468	0.727	0.888
## Enthusiastic -> Activation_Anchor	15.200	0.684	0.870
## Irritable -> Activation_Anchor	-4.418	-0.619	-0.204
## Nervous -> Activation_Anchor	-4.971	-0.653	-0.262
## PA -> G_Factor_Reflective	19.543	0.827	0.942
## NA -> G_Factor_Reflective	-7.950	-0.794	-0.488

### 3.9 Reflective with lavaan

Theoretical model does not work in BR (Brazil)

```
### 1. Two-Factor Correlated Model (Canonical Model)
#-----

two_factor_syntax <- '
  PAF =~ Active + Attentive + Determined + Excited + Interested + Proud +
    Alert + Enthusiastic + Strong + Inspired

  NAF =~ Ashamed + Distressed + Guilty + Irritable + Scared + Hostile +
    Jittery + Nervous + Afraid + Upset
'

fit_two_factor <- cfa(
  two_factor_syntax,
  data = panas_data,
  ordered = TRUE,
  estimator = "WLSMV",
  std.lv = TRUE
)

fitMeasures(fit_two_factor, c("chisq", "df", "pvalue", "cfi", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper"))

##          chisq          df          pvalue          cfi          rmsea
##          953.755        169.000          0.000          0.970          0.101
## rmsea.ci.lower rmsea.ci.upper
##          0.095          0.107

semTools::compRelSEM(fit_two_factor)

##   PAF   NAF
## 0.913 0.911
```

##Theoretical model fit adjustment Literature suggests “Alert” loads on both factors.

```
### 2. Two-Factor Model with Cross-Loading for "Alert"
#-----
```

```

crossload_syntax <- '
  PAF =~ Active + Attentive + Determined + Excited + Interested + Proud +
    Alert + Enthusiastic + Strong + Inspired

  NAF =~ Ashamed + Distressed + Guilty + Irritable + Scared + Hostile +
    Jittery + Nervous + Afraid + Upset + Alert # Cross-loading added
,

fit_crossload <- cfa(
  crossload_syntax,
  data = panas_data,
  ordered = TRUE,
  estimator = "WLSMV",
  std.lv = TRUE
)

fitMeasures(fit_crossload, c("chisq", "df", "pvalue", "cfi", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper"))

```

```

##          chisq          df          pvalue          cfi          rmsea
##      638.313      168.000          0.000          0.982          0.078
## rmsea.ci.lower rmsea.ci.upper
##          0.072          0.085

```

```
summary(fit_crossload, fit.measures = TRUE, standardized = TRUE)
```

```

## lavaan 0.6-20 ended normally after 23 iterations
##
##      Estimator          DWLS
##      Optimization method    NLMINB
##      Number of model parameters    102
##
##      Number of observations    457
##
## Model Test User Model:
##
##              Standard      Scaled
##      Test Statistic    638.313    682.235
##      Degrees of freedom    168      168
##      P-value (Chi-square)    0.000    0.000
##      Scaling correction factor    1.058
##      Shift parameter    78.647
##      simple second-order correction
##
## Model Test Baseline Model:
##
##      Test statistic    26632.140    8829.609
##      Degrees of freedom    190      190
##      P-value    0.000    0.000
##      Scaling correction factor    3.061
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)    0.982    0.940

```

```

## Tucker-Lewis Index (TLI)                0.980      0.933
##
## Robust Comparative Fit Index (CFI)        0.845
## Robust Tucker-Lewis Index (TLI)          0.825
##
## Root Mean Square Error of Approximation:
##
## RMSEA                0.078      0.082
## 90 Percent confidence interval - lower    0.072      0.076
## 90 Percent confidence interval - upper    0.085      0.088
## P-value H_0: RMSEA <= 0.050              0.000      0.000
## P-value H_0: RMSEA >= 0.080              0.344      0.697
##
## Robust RMSEA                0.108
## 90 Percent confidence interval - lower    0.101
## 90 Percent confidence interval - upper    0.115
## P-value H_0: Robust RMSEA <= 0.050      0.000
## P-value H_0: Robust RMSEA >= 0.080      1.000
##
## Standardized Root Mean Square Residual:
##
## SRMR                0.072      0.072
##
## Parameter Estimates:
##
## Parameterization          Delta
## Standard errors          Robust.sem
## Information              Expected
## Information saturated (h1) model    Unstructured
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## PAf =~
## Active      0.738   0.025  29.384   0.000   0.738   0.738
## Attentive   0.727   0.025  29.429   0.000   0.727   0.727
## Determined  0.787   0.023  33.952   0.000   0.787   0.787
## Excited     0.828   0.016  51.124   0.000   0.828   0.828
## Interested  0.790   0.021  37.248   0.000   0.790   0.790
## Proud       0.774   0.019  40.463   0.000   0.774   0.774
## Alert       0.479   0.034  14.015   0.000   0.479   0.479
## Enthusiastic 0.840   0.015  55.769   0.000   0.840   0.840
## Strong      0.722   0.023  31.430   0.000   0.722   0.722
## Inspired    0.726   0.022  33.144   0.000   0.726   0.726
## N Af =~
## Ashamed     0.524   0.036  14.629   0.000   0.524   0.524
## Distressed  0.790   0.019  40.603   0.000   0.790   0.790
## Guilty      0.690   0.029  23.874   0.000   0.690   0.690
## Irritable   0.721   0.024  29.952   0.000   0.721   0.721
## Scared      0.781   0.022  36.113   0.000   0.781   0.781
## Hostile     0.576   0.034  16.874   0.000   0.576   0.576
## Jittery     0.687   0.027  25.636   0.000   0.687   0.687
## Nervous     0.848   0.017  49.936   0.000   0.848   0.848
## Afraid      0.727   0.026  27.686   0.000   0.727   0.727
## Upset       0.785   0.021  37.766   0.000   0.785   0.785

```

```

##      Alert          0.361    0.038    9.630    0.000    0.361    0.361
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      P Af ~ ~
##      N Af      -0.144    0.048   -2.983    0.003   -0.144   -0.144
##
## Thresholds:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      Active|t1   -1.872    0.117  -16.056    0.000   -1.872   -1.872
##      Active|t2   -1.399    0.085  -16.425    0.000   -1.399   -1.399
##      Active|t3   -0.885    0.068  -13.038    0.000   -0.885   -0.885
##      Active|t4    0.488    0.061    7.955    0.000    0.488    0.488
##      Attentive|t1 -1.904    0.120  -15.923    0.000   -1.904   -1.904
##      Attentive|t2 -1.399    0.085  -16.425    0.000   -1.399   -1.399
##      Attentive|t3 -0.829    0.067  -12.441    0.000   -0.829   -0.829
##      Attentive|t4  0.732    0.065   11.305    0.000    0.732    0.732
##      Determined|t1 -1.939    0.123  -15.768    0.000   -1.939   -1.939
##      Determined|t2 -1.303    0.081  -16.102    0.000   -1.303   -1.303
##      Determined|t3 -0.622    0.063   -9.872    0.000   -0.622   -0.622
##      Determined|t4  0.662    0.064   10.413    0.000    0.662    0.662
##      Excited|t1   -1.939    0.123  -15.768    0.000   -1.939   -1.939
##      Excited|t2   -1.266    0.079  -15.936    0.000   -1.266   -1.266
##      Excited|t3   -0.350    0.060   -5.829    0.000   -0.350   -0.350
##      Excited|t4    0.740    0.065   11.394    0.000    0.740    0.740
##      Interested|t1 -1.872    0.117  -16.056    0.000   -1.872   -1.872
##      Interested|t2 -1.444    0.087  -16.529    0.000   -1.444   -1.444
##      Interested|t3 -0.732    0.065  -11.305    0.000   -0.732   -0.732
##      Interested|t4  0.622    0.063    9.872    0.000    0.622    0.622
##      Proud|t1     -1.544    0.093  -16.650    0.000   -1.544   -1.544
##      Proud|t2     -0.885    0.068  -13.038    0.000   -0.885   -0.885
##      Proud|t3     -0.140    0.059   -2.382    0.017   -0.140   -0.140
##      Proud|t4      0.869    0.067   12.869    0.000    0.869    0.869
##      Alert|t1     -1.399    0.085  -16.425    0.000   -1.399   -1.399
##      Alert|t2     -0.943    0.069  -13.619    0.000   -0.943   -0.943
##      Alert|t3     -0.235    0.059   -3.968    0.000   -0.235   -0.235
##      Alert|t4      0.987    0.070   14.024    0.000    0.987    0.987
##      Enthusiastc|t1 -1.733    0.105  -16.481    0.000   -1.733   -1.733
##      Enthusiastc|t2 -1.061    0.072  -14.646    0.000   -1.061   -1.061
##      Enthusiastc|t3 -0.286    0.060   -4.806    0.000   -0.286   -0.286
##      Enthusiastc|t4  0.837    0.067   12.527    0.000    0.837    0.837
##      Strong|t1     -1.509    0.091  -16.625    0.000   -1.509   -1.509
##      Strong|t2     -0.951    0.069  -13.701    0.000   -0.951   -0.951
##      Strong|t3     -0.151    0.059   -2.569    0.010   -0.151   -0.151
##      Strong|t4      0.918    0.069   13.372    0.000    0.918    0.918
##      Inspired|t1   -1.758    0.107  -16.422    0.000   -1.758   -1.758
##      Inspired|t2   -1.061    0.072  -14.646    0.000   -1.061   -1.061
##      Inspired|t3   -0.190    0.059   -3.222    0.001   -0.190   -0.190
##      Inspired|t4    0.747    0.065   11.482    0.000    0.747    0.747
##      Ashamed|t1    -0.635    0.063  -10.053    0.000   -0.635   -0.635
##      Ashamed|t2     0.074    0.059    1.262    0.207    0.074    0.074
##      Ashamed|t3     0.814    0.066   12.269    0.000    0.814    0.814
##      Ashamed|t4     2.016    0.131   15.377    0.000    2.016    2.016
##      Distressed|t1 -1.090    0.073  -14.870    0.000   -1.090   -1.090

```

##	Distressed t2	-0.488	0.061	-7.955	0.000	-0.488	-0.488
##	Distressed t3	0.030	0.059	0.514	0.607	0.030	0.030
##	Distressed t4	1.141	0.075	15.229	0.000	1.141	1.141
##	Guilty t1	-0.602	0.063	-9.600	0.000	-0.602	-0.602
##	Guilty t2	0.008	0.059	0.140	0.889	0.008	0.008
##	Guilty t3	0.690	0.064	10.772	0.000	0.690	0.690
##	Guilty t4	1.621	0.097	16.641	0.000	1.621	1.621
##	Irritable t1	-1.303	0.081	-16.102	0.000	-1.303	-1.303
##	Irritable t2	-0.451	0.061	-7.402	0.000	-0.451	-0.451
##	Irritable t3	0.163	0.059	2.756	0.006	0.163	0.163
##	Irritable t4	1.356	0.083	16.299	0.000	1.356	1.356
##	Scared t1	-0.877	0.068	-12.953	0.000	-0.877	-0.877
##	Scared t2	-0.163	0.059	-2.756	0.006	-0.163	-0.163
##	Scared t3	0.344	0.060	5.736	0.000	0.344	0.344
##	Scared t4	1.184	0.076	15.501	0.000	1.184	1.184
##	Hostile t1	-0.367	0.060	-6.107	0.000	-0.367	-0.367
##	Hostile t2	0.275	0.060	4.620	0.000	0.275	0.275
##	Hostile t3	1.090	0.073	14.870	0.000	1.090	1.090
##	Hostile t4	1.976	0.127	15.588	0.000	1.976	1.976
##	Jittery t1	-1.329	0.082	-16.204	0.000	-1.329	-1.329
##	Jittery t2	-0.635	0.063	-10.053	0.000	-0.635	-0.635
##	Jittery t3	-0.052	0.059	-0.888	0.375	-0.052	-0.052
##	Jittery t4	0.960	0.070	13.782	0.000	0.960	0.960
##	Nervous t1	-1.042	0.072	-14.494	0.000	-1.042	-1.042
##	Nervous t2	-0.367	0.060	-6.107	0.000	-0.367	-0.367
##	Nervous t3	0.213	0.059	3.595	0.000	0.213	0.213
##	Nervous t4	1.195	0.077	15.567	0.000	1.195	1.195
##	Afraid t1	-0.207	0.059	-3.502	0.000	-0.207	-0.207
##	Afraid t2	0.421	0.061	6.940	0.000	0.421	0.421
##	Afraid t3	1.120	0.074	15.088	0.000	1.120	1.120
##	Afraid t4	1.758	0.107	16.422	0.000	1.758	1.758
##	Upset t1	-0.877	0.068	-12.953	0.000	-0.877	-0.877
##	Upset t2	-0.247	0.059	-4.155	0.000	-0.247	-0.247
##	Upset t3	0.275	0.060	4.620	0.000	0.275	0.275
##	Upset t4	1.241	0.078	15.818	0.000	1.241	1.241
##							
##	Variances:						
##		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
##	.Active	0.456				0.456	0.456
##	.Attentive	0.471				0.471	0.471
##	.Determined	0.380				0.380	0.380
##	.Excited	0.315				0.315	0.315
##	.Interested	0.376				0.376	0.376
##	.Proud	0.401				0.401	0.401
##	.Alert	0.690				0.690	0.690
##	.Enthusiastic	0.294				0.294	0.294
##	.Strong	0.479				0.479	0.479
##	.Inspired	0.473				0.473	0.473
##	.Ashamed	0.725				0.725	0.725
##	.Distressed	0.377				0.377	0.377
##	.Guilty	0.525				0.525	0.525
##	.Irritable	0.480				0.480	0.480
##	.Scared	0.390				0.390	0.390
##	.Hostile	0.668				0.668	0.668

```
##      .Jittery      0.528      0.528      0.528
##      .Nervous      0.280      0.280      0.280
##      .Afraid       0.471      0.471      0.471
##      .Upset        0.384      0.384      0.384
##      PAF           1.000      1.000      1.000
##      NAF           1.000      1.000      1.000
```

```
semTools::compRelSEM(fit_crossload)
```

```
##      PAF      NAF
## 0.934 0.922
```

### 3.10 Reflective bifactor model fits the data better

```
### 3. Orthogonal Bifactor Model
```

```
#-----
```

```
bifactor_syntax <- '
  G_Factor =~ Active + Ashamed + Attentive + Distressed + Determined + Guilty +
              Excited + Irritable + Interested + Scared + Proud + Hostile +
              Alert + Jittery + Enthusiastic + Nervous + Strong + Afraid +
              Inspired + Upset

  PAF =~ Active + Attentive + Determined + Excited + Interested + Proud +
         Alert + Enthusiastic + Strong + Inspired

  NAF =~ Ashamed + Distressed + Guilty + Irritable + Scared + Hostile +
         Jittery + Nervous + Afraid + Upset
,
```

```
fit_bifactor_orthogonal <- cfa(
  bifactor_syntax,
  data = panas_data,
  ordered = TRUE,
  orthogonal = TRUE,
  estimator = "WLSMV",
  std.lv = TRUE
)
```

```
fitMeasures(fit_bifactor_orthogonal, c("chisq", "df", "pvalue", "cfi", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper"))
```

```
##      chisq      df      pvalue      cfi      rmsea
##      503.450    150.000      0.000      0.987      0.072
## rmsea.ci.lower rmsea.ci.upper
##      0.065      0.079
```

```
summary(fit_bifactor_orthogonal, standardized = TRUE)
```

```
## lavaan 0.6-20 ended normally after 64 iterations
##
```

```

## Estimator DWLS
## Optimization method NLMINB
## Number of model parameters 120
##
## Number of observations 457
##
## Model Test User Model:
## Standard Scaled
## Test Statistic 503.450 682.823
## Degrees of freedom 150 150
## P-value (Chi-square) 0.000 0.000
## Scaling correction factor 0.815
## Shift parameter 65.010
## simple second-order correction
##
## Parameter Estimates:
##
## Parameterization Delta
## Standard errors Robust.sem
## Information Expected
## Information saturated (h1) model Unstructured
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## G_Factor =~
## Active 0.279 0.060 4.655 0.000 0.279 0.279
## Ashamed -0.353 0.072 -4.901 0.000 -0.353 -0.353
## Attentive 0.169 0.063 2.684 0.007 0.169 0.169
## Distressed -0.517 0.072 -7.207 0.000 -0.517 -0.517
## Determined 0.226 0.060 3.751 0.000 0.226 0.226
## Guilty -0.532 0.062 -8.606 0.000 -0.532 -0.532
## Excited 0.300 0.055 5.411 0.000 0.300 0.300
## Irritable -0.154 0.092 -1.672 0.094 -0.154 -0.154
## Interested 0.111 0.065 1.707 0.088 0.111 0.111
## Scared -0.564 0.068 -8.268 0.000 -0.564 -0.564
## Proud 0.240 0.057 4.206 0.000 0.240 0.240
## Hostile -0.387 0.065 -5.924 0.000 -0.387 -0.387
## Alert -0.407 0.077 -5.294 0.000 -0.407 -0.407
## Jittery -0.349 0.074 -4.711 0.000 -0.349 -0.349
## Enthusiastic 0.230 0.057 4.022 0.000 0.230 0.230
## Nervous -0.379 0.084 -4.531 0.000 -0.379 -0.379
## Strong 0.085 0.060 1.405 0.160 0.085 0.085
## Afraid -0.758 0.059 -12.867 0.000 -0.758 -0.758
## Inspired 0.185 0.060 3.056 0.002 0.185 0.185
## Upset -0.443 0.073 -6.097 0.000 -0.443 -0.443
## PAF =~
## Active 0.687 0.031 22.269 0.000 0.687 0.687
## Attentive 0.709 0.027 26.374 0.000 0.709 0.709
## Determined 0.755 0.026 29.185 0.000 0.755 0.755
## Excited 0.775 0.024 32.547 0.000 0.775 0.775
## Interested 0.793 0.023 34.580 0.000 0.793 0.793
## Proud 0.736 0.024 30.594 0.000 0.736 0.736
## Alert 0.552 0.043 12.974 0.000 0.552 0.552
## Enthusiastic 0.807 0.020 40.888 0.000 0.807 0.807

```

##	Strong	0.728	0.022	33.355	0.000	0.728	0.728
##	Inspired	0.701	0.024	28.810	0.000	0.701	0.701
##	Naf =~						
##	Ashamed	0.386	0.061	6.312	0.000	0.386	0.386
##	Distressed	0.599	0.060	9.915	0.000	0.599	0.599
##	Guilty	0.455	0.063	7.245	0.000	0.455	0.455
##	Irritable	0.800	0.040	19.909	0.000	0.800	0.800
##	Scared	0.550	0.065	8.490	0.000	0.550	0.550
##	Hostile	0.424	0.058	7.301	0.000	0.424	0.424
##	Jittery	0.597	0.048	12.339	0.000	0.597	0.597
##	Nervous	0.779	0.042	18.359	0.000	0.779	0.779
##	Afraid	0.338	0.079	4.258	0.000	0.338	0.338
##	Upset	0.650	0.048	13.518	0.000	0.650	0.650
##							
##	Covariances:						
##		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
##	G_Factor ~~						
##	PAf	0.000				0.000	0.000
##	Naf	0.000				0.000	0.000
##	PAf ~~						
##	Naf	0.000				0.000	0.000
##							
##	Thresholds:						
##		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
##	Active t1	-1.872	0.117	-16.056	0.000	-1.872	-1.872
##	Active t2	-1.399	0.085	-16.425	0.000	-1.399	-1.399
##	Active t3	-0.885	0.068	-13.038	0.000	-0.885	-0.885
##	Active t4	0.488	0.061	7.955	0.000	0.488	0.488
##	Ashamed t1	-0.635	0.063	-10.053	0.000	-0.635	-0.635
##	Ashamed t2	0.074	0.059	1.262	0.207	0.074	0.074
##	Ashamed t3	0.814	0.066	12.269	0.000	0.814	0.814
##	Ashamed t4	2.016	0.131	15.377	0.000	2.016	2.016
##	Attentive t1	-1.904	0.120	-15.923	0.000	-1.904	-1.904
##	Attentive t2	-1.399	0.085	-16.425	0.000	-1.399	-1.399
##	Attentive t3	-0.829	0.067	-12.441	0.000	-0.829	-0.829
##	Attentive t4	0.732	0.065	11.305	0.000	0.732	0.732
##	Distressed t1	-1.090	0.073	-14.870	0.000	-1.090	-1.090
##	Distressed t2	-0.488	0.061	-7.955	0.000	-0.488	-0.488
##	Distressed t3	0.030	0.059	0.514	0.607	0.030	0.030
##	Distressed t4	1.141	0.075	15.229	0.000	1.141	1.141
##	Determined t1	-1.939	0.123	-15.768	0.000	-1.939	-1.939
##	Determined t2	-1.303	0.081	-16.102	0.000	-1.303	-1.303
##	Determined t3	-0.622	0.063	-9.872	0.000	-0.622	-0.622
##	Determined t4	0.662	0.064	10.413	0.000	0.662	0.662
##	Guilty t1	-0.602	0.063	-9.600	0.000	-0.602	-0.602
##	Guilty t2	0.008	0.059	0.140	0.889	0.008	0.008
##	Guilty t3	0.690	0.064	10.772	0.000	0.690	0.690
##	Guilty t4	1.621	0.097	16.641	0.000	1.621	1.621
##	Excited t1	-1.939	0.123	-15.768	0.000	-1.939	-1.939
##	Excited t2	-1.266	0.079	-15.936	0.000	-1.266	-1.266
##	Excited t3	-0.350	0.060	-5.829	0.000	-0.350	-0.350
##	Excited t4	0.740	0.065	11.394	0.000	0.740	0.740
##	Irritable t1	-1.303	0.081	-16.102	0.000	-1.303	-1.303
##	Irritable t2	-0.451	0.061	-7.402	0.000	-0.451	-0.451



##	Irritable t3	0.163	0.059	2.756	0.006	0.163	0.163
##	Irritable t4	1.356	0.083	16.299	0.000	1.356	1.356
##	Interested t1	-1.872	0.117	-16.056	0.000	-1.872	-1.872
##	Interested t2	-1.444	0.087	-16.529	0.000	-1.444	-1.444
##	Interested t3	-0.732	0.065	-11.305	0.000	-0.732	-0.732
##	Interested t4	0.622	0.063	9.872	0.000	0.622	0.622
##	Scared t1	-0.877	0.068	-12.953	0.000	-0.877	-0.877
##	Scared t2	-0.163	0.059	-2.756	0.006	-0.163	-0.163
##	Scared t3	0.344	0.060	5.736	0.000	0.344	0.344
##	Scared t4	1.184	0.076	15.501	0.000	1.184	1.184
##	Proud t1	-1.544	0.093	-16.650	0.000	-1.544	-1.544
##	Proud t2	-0.885	0.068	-13.038	0.000	-0.885	-0.885
##	Proud t3	-0.140	0.059	-2.382	0.017	-0.140	-0.140
##	Proud t4	0.869	0.067	12.869	0.000	0.869	0.869
##	Hostile t1	-0.367	0.060	-6.107	0.000	-0.367	-0.367
##	Hostile t2	0.275	0.060	4.620	0.000	0.275	0.275
##	Hostile t3	1.090	0.073	14.870	0.000	1.090	1.090
##	Hostile t4	1.976	0.127	15.588	0.000	1.976	1.976
##	Alert t1	-1.399	0.085	-16.425	0.000	-1.399	-1.399
##	Alert t2	-0.943	0.069	-13.619	0.000	-0.943	-0.943
##	Alert t3	-0.235	0.059	-3.968	0.000	-0.235	-0.235
##	Alert t4	0.987	0.070	14.024	0.000	0.987	0.987
##	Jittery t1	-1.329	0.082	-16.204	0.000	-1.329	-1.329
##	Jittery t2	-0.635	0.063	-10.053	0.000	-0.635	-0.635
##	Jittery t3	-0.052	0.059	-0.888	0.375	-0.052	-0.052
##	Jittery t4	0.960	0.070	13.782	0.000	0.960	0.960
##	Enthusiastc t1	-1.733	0.105	-16.481	0.000	-1.733	-1.733
##	Enthusiastc t2	-1.061	0.072	-14.646	0.000	-1.061	-1.061
##	Enthusiastc t3	-0.286	0.060	-4.806	0.000	-0.286	-0.286
##	Enthusiastc t4	0.837	0.067	12.527	0.000	0.837	0.837
##	Nervous t1	-1.042	0.072	-14.494	0.000	-1.042	-1.042
##	Nervous t2	-0.367	0.060	-6.107	0.000	-0.367	-0.367
##	Nervous t3	0.213	0.059	3.595	0.000	0.213	0.213
##	Nervous t4	1.195	0.077	15.567	0.000	1.195	1.195
##	Strong t1	-1.509	0.091	-16.625	0.000	-1.509	-1.509
##	Strong t2	-0.951	0.069	-13.701	0.000	-0.951	-0.951
##	Strong t3	-0.151	0.059	-2.569	0.010	-0.151	-0.151
##	Strong t4	0.918	0.069	13.372	0.000	0.918	0.918
##	Afraid t1	-0.207	0.059	-3.502	0.000	-0.207	-0.207
##	Afraid t2	0.421	0.061	6.940	0.000	0.421	0.421
##	Afraid t3	1.120	0.074	15.088	0.000	1.120	1.120
##	Afraid t4	1.758	0.107	16.422	0.000	1.758	1.758
##	Inspired t1	-1.758	0.107	-16.422	0.000	-1.758	-1.758
##	Inspired t2	-1.061	0.072	-14.646	0.000	-1.061	-1.061
##	Inspired t3	-0.190	0.059	-3.222	0.001	-0.190	-0.190
##	Inspired t4	0.747	0.065	11.482	0.000	0.747	0.747
##	Upset t1	-0.877	0.068	-12.953	0.000	-0.877	-0.877
##	Upset t2	-0.247	0.059	-4.155	0.000	-0.247	-0.247
##	Upset t3	0.275	0.060	4.620	0.000	0.275	0.275
##	Upset t4	1.241	0.078	15.818	0.000	1.241	1.241
##							
##	Variances:						
##		Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
##	.Active	0.450				0.450	0.450

##	.Ashamed	0.726	0.726	0.726
##	.Attentive	0.469	0.469	0.469
##	.Distressed	0.374	0.374	0.374
##	.Determined	0.380	0.380	0.380
##	.Guilty	0.510	0.510	0.510
##	.Excited	0.309	0.309	0.309
##	.Irritable	0.337	0.337	0.337
##	.Interested	0.358	0.358	0.358
##	.Scared	0.380	0.380	0.380
##	.Proud	0.401	0.401	0.401
##	.Hostile	0.670	0.670	0.670
##	.Alert	0.530	0.530	0.530
##	.Jittery	0.521	0.521	0.521
##	.Enthusiastic	0.296	0.296	0.296
##	.Nervous	0.250	0.250	0.250
##	.Strong	0.463	0.463	0.463
##	.Afraid	0.311	0.311	0.311
##	.Inspired	0.474	0.474	0.474
##	.Upset	0.382	0.382	0.382
##	G_Factor	1.000	1.000	1.000
##	PAf	1.000	1.000	1.000
##	NAf	1.000	1.000	1.000

```
semTools::compRelSEM(fit_bifactor_orthogonal)
```

##	G_Factor	PAf	NAf
##	0.124	0.893	0.556

### 3.11 Constrained bifactor model

We apply constraints for parsimony.

```
### 4. Constrained Bifactor Model (for Parsimony)
#-----

constrained_bifactor_syntax <- '
  G_Factor =~ Active + 0*Ashamed + Attentive + 0*Distressed + Determined +
    0*Guilty + Excited + 0*Irritable + Interested + 0*Scared +
    Proud + 0*Hostile + Alert + 0*Jittery +
    Enthusiastic + 0*Nervous + Strong + Afraid +
    Inspired + 0*Upset

  PAf =~ 0*Active + 0*Attentive + 0*Determined + Excited + Interested + Proud +
    0*Alert + Enthusiastic + Strong + Inspired

  NAf =~ Ashamed + Distressed + Guilty + Irritable + Scared + Hostile +
    Jittery + Nervous + Afraid + Upset + Alert
'

fit_bifactor_constrained <- cfa(
  constrained_bifactor_syntax,
  data = panas_data,
```

```

ordered = TRUE,
orthogonal = TRUE,
estimator = "WLSMV",
std.lv = TRUE
)

fitMeasures(fit_bifactor_constrained, c("chisq", "df", "pvalue", "cfi", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper"))

```

```

##          chisq          df          pvalue          cfi          rmsea
##      591.050      162.000          0.000          0.984          0.076
## rmsea.ci.lower rmsea.ci.upper
##          0.070          0.083

```

```
summary(fit_bifactor_constrained, standardized = TRUE)
```

```

## lavaan 0.6-20 ended normally after 32 iterations
##
##      Estimator                      DWLS
##      Optimization method          NLMINB
##      Number of model parameters      108
##
##      Number of observations          457
##
## Model Test User Model:
##
##              Standard      Scaled
##      Test Statistic      591.050    357.748
##      Degrees of freedom      162      162
##      P-value (Chi-square)      0.000      0.000
##      Scaling correction factor      2.423
##      Shift parameter          113.830
##      simple second-order correction
##
## Parameter Estimates:
##
##      Parameterization          Delta
##      Standard errors          Robust.sem
##      Information          Expected
##      Information saturated (h1) model      Unstructured
##
## Latent Variables:
##
##              Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##      G_Factor =~
##      Active          0.795    0.024   33.147    0.000    0.795    0.795
##      Ashamed          0.000          0.000          0.000    0.000    0.000    0.000
##      Attentive        0.780    0.023   34.278    0.000    0.780    0.780
##      Distressed        0.000          0.000          0.000    0.000    0.000    0.000
##      Determined        0.859    0.022   39.063    0.000    0.859    0.859
##      Guilty            0.000          0.000          0.000    0.000    0.000    0.000
##      Excited          0.687    0.027   25.396    0.000    0.687    0.687
##      Irritable          0.000          0.000          0.000    0.000    0.000    0.000
##      Interested        0.694    0.028   24.351    0.000    0.694    0.694
##      Scared            0.000          0.000          0.000    0.000    0.000    0.000

```

```

##      Proud      0.687    0.026   26.075    0.000    0.687    0.687
##      Hostile      0.000
##      Alert       0.464    0.038   12.084    0.000    0.464    0.464
##      Jittery      0.000
##      Enthusiastic 0.668    0.027   24.995    0.000    0.668    0.668
##      Nervous      0.000
##      Strong       0.620    0.030   20.469    0.000    0.620    0.620
##      Afraid      -0.315    0.049   -6.467    0.000   -0.315   -0.315
##      Inspired     0.579    0.032   18.274    0.000    0.579    0.579
##      Upset        0.000
##      PAF =~
##      Active       0.000
##      Attentive    0.000
##      Determined   0.000
##      Excited      0.483    0.034   14.324    0.000    0.483    0.483
##      Interested   0.404    0.037   11.064    0.000    0.404    0.404
##      Proud        0.358    0.041    8.668    0.000    0.358    0.358
##      Alert        0.000
##      Enthusiastic 0.564    0.031   18.304    0.000    0.564    0.564
##      Strong       0.387    0.040    9.743    0.000    0.387    0.387
##      Inspired     0.477    0.037   13.045    0.000    0.477    0.477
##      NAF =~
##      Ashamed      0.524    0.036   14.699    0.000    0.524    0.524
##      Distressed   0.784    0.020   39.943    0.000    0.784    0.784
##      Guilty       0.681    0.028   23.932    0.000    0.681    0.681
##      Irritable    0.730    0.024   31.024    0.000    0.730    0.730
##      Scared       0.782    0.021   36.825    0.000    0.782    0.782
##      Hostile      0.581    0.034   17.314    0.000    0.581    0.581
##      Jittery      0.695    0.026   26.494    0.000    0.695    0.695
##      Nervous      0.855    0.016   52.130    0.000    0.855    0.855
##      Afraid       0.714    0.027   26.328    0.000    0.714    0.714
##      Upset        0.779    0.021   37.085    0.000    0.779    0.779
##      Alert        0.310    0.040    7.665    0.000    0.310    0.310
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      G_Factor ~~
##      PAF        0.000
##      NAF        0.000
##      PAF ~~
##      NAF        0.000
##
## Thresholds:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      Active|t1  -1.872    0.117  -16.056    0.000   -1.872   -1.872
##      Active|t2  -1.399    0.085  -16.425    0.000   -1.399   -1.399
##      Active|t3  -0.885    0.068  -13.038    0.000   -0.885   -0.885
##      Active|t4    0.488    0.061    7.955    0.000    0.488    0.488
##      Ashamed|t1 -0.635    0.063  -10.053    0.000   -0.635   -0.635
##      Ashamed|t2  0.074    0.059    1.262    0.207    0.074    0.074
##      Ashamed|t3  0.814    0.066   12.269    0.000    0.814    0.814
##      Ashamed|t4  2.016    0.131   15.377    0.000    2.016    2.016
##      Attentive|t1 -1.904    0.120  -15.923    0.000   -1.904   -1.904
##      Attentive|t2 -1.399    0.085  -16.425    0.000   -1.399   -1.399

```

##	Attentive t3	-0.829	0.067	-12.441	0.000	-0.829	-0.829
##	Attentive t4	0.732	0.065	11.305	0.000	0.732	0.732
##	Distressed t1	-1.090	0.073	-14.870	0.000	-1.090	-1.090
##	Distressed t2	-0.488	0.061	-7.955	0.000	-0.488	-0.488
##	Distressed t3	0.030	0.059	0.514	0.607	0.030	0.030
##	Distressed t4	1.141	0.075	15.229	0.000	1.141	1.141
##	Determined t1	-1.939	0.123	-15.768	0.000	-1.939	-1.939
##	Determined t2	-1.303	0.081	-16.102	0.000	-1.303	-1.303
##	Determined t3	-0.622	0.063	-9.872	0.000	-0.622	-0.622
##	Determined t4	0.662	0.064	10.413	0.000	0.662	0.662
##	Guilty t1	-0.602	0.063	-9.600	0.000	-0.602	-0.602
##	Guilty t2	0.008	0.059	0.140	0.889	0.008	0.008
##	Guilty t3	0.690	0.064	10.772	0.000	0.690	0.690
##	Guilty t4	1.621	0.097	16.641	0.000	1.621	1.621
##	Excited t1	-1.939	0.123	-15.768	0.000	-1.939	-1.939
##	Excited t2	-1.266	0.079	-15.936	0.000	-1.266	-1.266
##	Excited t3	-0.350	0.060	-5.829	0.000	-0.350	-0.350
##	Excited t4	0.740	0.065	11.394	0.000	0.740	0.740
##	Irritable t1	-1.303	0.081	-16.102	0.000	-1.303	-1.303
##	Irritable t2	-0.451	0.061	-7.402	0.000	-0.451	-0.451
##	Irritable t3	0.163	0.059	2.756	0.006	0.163	0.163
##	Irritable t4	1.356	0.083	16.299	0.000	1.356	1.356
##	Interested t1	-1.872	0.117	-16.056	0.000	-1.872	-1.872
##	Interested t2	-1.444	0.087	-16.529	0.000	-1.444	-1.444
##	Interested t3	-0.732	0.065	-11.305	0.000	-0.732	-0.732
##	Interested t4	0.622	0.063	9.872	0.000	0.622	0.622
##	Scared t1	-0.877	0.068	-12.953	0.000	-0.877	-0.877
##	Scared t2	-0.163	0.059	-2.756	0.006	-0.163	-0.163
##	Scared t3	0.344	0.060	5.736	0.000	0.344	0.344
##	Scared t4	1.184	0.076	15.501	0.000	1.184	1.184
##	Proud t1	-1.544	0.093	-16.650	0.000	-1.544	-1.544
##	Proud t2	-0.885	0.068	-13.038	0.000	-0.885	-0.885
##	Proud t3	-0.140	0.059	-2.382	0.017	-0.140	-0.140
##	Proud t4	0.869	0.067	12.869	0.000	0.869	0.869
##	Hostile t1	-0.367	0.060	-6.107	0.000	-0.367	-0.367
##	Hostile t2	0.275	0.060	4.620	0.000	0.275	0.275
##	Hostile t3	1.090	0.073	14.870	0.000	1.090	1.090
##	Hostile t4	1.976	0.127	15.588	0.000	1.976	1.976
##	Alert t1	-1.399	0.085	-16.425	0.000	-1.399	-1.399
##	Alert t2	-0.943	0.069	-13.619	0.000	-0.943	-0.943
##	Alert t3	-0.235	0.059	-3.968	0.000	-0.235	-0.235
##	Alert t4	0.987	0.070	14.024	0.000	0.987	0.987
##	Jittery t1	-1.329	0.082	-16.204	0.000	-1.329	-1.329
##	Jittery t2	-0.635	0.063	-10.053	0.000	-0.635	-0.635
##	Jittery t3	-0.052	0.059	-0.888	0.375	-0.052	-0.052
##	Jittery t4	0.960	0.070	13.782	0.000	0.960	0.960
##	Enthusiastic t1	-1.733	0.105	-16.481	0.000	-1.733	-1.733
##	Enthusiastic t2	-1.061	0.072	-14.646	0.000	-1.061	-1.061
##	Enthusiastic t3	-0.286	0.060	-4.806	0.000	-0.286	-0.286
##	Enthusiastic t4	0.837	0.067	12.527	0.000	0.837	0.837
##	Nervous t1	-1.042	0.072	-14.494	0.000	-1.042	-1.042
##	Nervous t2	-0.367	0.060	-6.107	0.000	-0.367	-0.367
##	Nervous t3	0.213	0.059	3.595	0.000	0.213	0.213
##	Nervous t4	1.195	0.077	15.567	0.000	1.195	1.195

```

##      Strong|t1      -1.509    0.091   -16.625    0.000   -1.509   -1.509
##      Strong|t2      -0.951    0.069   -13.701    0.000   -0.951   -0.951
##      Strong|t3      -0.151    0.059    -2.569    0.010   -0.151   -0.151
##      Strong|t4       0.918    0.069    13.372    0.000    0.918    0.918
##      Afraid|t1      -0.207    0.059    -3.502    0.000   -0.207   -0.207
##      Afraid|t2       0.421    0.061     6.940    0.000    0.421    0.421
##      Afraid|t3       1.120    0.074    15.088    0.000    1.120    1.120
##      Afraid|t4       1.758    0.107    16.422    0.000    1.758    1.758
##      Inspired|t1     -1.758    0.107   -16.422    0.000   -1.758   -1.758
##      Inspired|t2     -1.061    0.072   -14.646    0.000   -1.061   -1.061
##      Inspired|t3     -0.190    0.059    -3.222    0.001   -0.190   -0.190
##      Inspired|t4      0.747    0.065    11.482    0.000    0.747    0.747
##      Upset|t1       -0.877    0.068   -12.953    0.000   -0.877   -0.877
##      Upset|t2       -0.247    0.059    -4.155    0.000   -0.247   -0.247
##      Upset|t3        0.275    0.060     4.620    0.000    0.275    0.275
##      Upset|t4        1.241    0.078    15.818    0.000    1.241    1.241
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .Active      0.367
##      .Ashamed      0.725
##      .Attentive     0.392
##      .Distressed    0.385
##      .Determined    0.262
##      .Guilty        0.537
##      .Excited       0.295
##      .Irritable     0.467
##      .Interested    0.355
##      .Scared        0.389
##      .Proud         0.400
##      .Hostile       0.663
##      .Alert         0.688
##      .Jittery       0.516
##      .Enthusiastic  0.235
##      .Nervous       0.268
##      .Strong        0.465
##      .Afraid        0.392
##      .Inspired      0.437
##      .Upset         0.394
##      G_Factor       1.000
##      PAF            1.000
##      NAF            1.000

```

```
semTools::compRelSEM(fit_bifactor_constrained)
```

```

## G_Factor      PAF      NAF
##      0.736      0.276      0.909

```

### 3.12 Second-order model test

### ### 5. Oblique Bifactor Model

#-----

```
oblique_bifactor_syntax <- bifactor_syntax
```

```
fit_bifactor_oblique <- cfa(  
  oblique_bifactor_syntax,  
  data = panas_data,  
  ordered = TRUE,  
  orthogonal = FALSE, # Allows specific factors to correlate  
  estimator = "WLSMV",  
  std.lv = TRUE  
)
```

```
## Warning: lavaan->lav_model_vcov():  
##   Could not compute standard errors! The information matrix could not be  
##   inverted. This may be a symptom that the model is not identified.
```

```
## Warning: lavaan->lav_test_satorra_bentler():  
##   could not invert information matrix needed for robust test statistic
```

```
## Warning: lavaan->lav_object_post_check():  
##   covariance matrix of latent variables is not positive definite ; use  
##   lavInspect(fit, "cov.lv") to investigate.
```

```
fitMeasures(fit_bifactor_oblique, c("chisq", "df", "pvalue", "cfi", "rmsea", "rmsea.ci.lower", "rmsea.ci.upper"))
```

```
## Warning: lavaan->lav_object_post_check():  
##   covariance matrix of latent variables is not positive definite ; use  
##   lavInspect(fit, "cov.lv") to investigate.  
## Warning: lavaan->lav_object_post_check():  
##   covariance matrix of latent variables is not positive definite ; use  
##   lavInspect(fit, "cov.lv") to investigate.
```

	chisq	df	pvalue	cfi	rmsea
	369.564	147.000	0.000	0.992	0.058
rmsea.ci.lower					
	0.050	0.065			

```
summary(fit_bifactor_oblique, standardized = TRUE)
```

```
## lavaan 0.6-20 ended normally after 87 iterations
```

```
##  
##   Estimator                      DWLS  
##   Optimization method           NLMINB  
##   Number of model parameters      123  
##  
##   Number of observations          457  
##  
## Model Test User Model:
```

```

##                               Standard      Scaled
## Test Statistic                369.564        NA
## Degrees of freedom              147          147
## P-value (Chi-square)            0.000        NA
## Scaling correction factor              NA
## Shift parameter                  NA
##
##
## Parameter Estimates:
##
## Parameterization                Delta
## Standard errors                Robust.sem
## Information                     Expected
## Information saturated (h1) model Unstructured
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## G_Factor =~
##   Active      0.662    NA        0.662   0.662
##   Ashamed     -0.134    NA       -0.134  -0.134
##   Attentive    0.624    NA        0.624   0.624
##   Distressed  -0.247    NA       -0.247  -0.247
##   Determined   0.688    NA        0.688   0.688
##   Guilty      -0.253    NA       -0.253  -0.253
##   Excited      0.739    NA        0.739   0.739
##   Irritable   -0.049    NA       -0.049  -0.049
##   Interested   0.652    NA        0.652   0.652
##   Scared      -0.193    NA       -0.193  -0.193
##   Proud       0.690    NA        0.690   0.690
##   Hostile     -0.098    NA       -0.098  -0.098
##   Alert       0.220    NA        0.220   0.220
##   Jittery     -0.060    NA       -0.060  -0.060
##   Enthusiastic 0.734    NA        0.734   0.734
##   Nervous     -0.089    NA       -0.089  -0.089
##   Strong      0.605    NA        0.605   0.605
##   Afraid     -0.376    NA       -0.376  -0.376
##   Inspired    0.636    NA        0.636   0.636
##   Upset      -0.249    NA       -0.249  -0.249
## PAf =~
##   Active      0.305    NA        0.305   0.305
##   Attentive    0.363    NA        0.363   0.363
##   Determined   0.364    NA        0.364   0.364
##   Excited      0.348    NA        0.348   0.348
##   Interested   0.448    NA        0.448   0.448
##   Proud       0.329    NA        0.329   0.329
##   Alert       0.476    NA        0.476   0.476
##   Enthusiastic 0.387    NA        0.387   0.387
##   Strong      0.387    NA        0.387   0.387
##   Inspired    0.327    NA        0.327   0.327
## NAf =~
##   Ashamed     0.445    NA        0.445   0.445
##   Distressed   0.638    NA        0.638   0.638
##   Guilty       0.528    NA        0.528   0.528
##   Irritable    0.711    NA        0.711   0.711

```



```

##      Scared          0.670      NA          0.670      0.670
##      Hostile         0.526      NA          0.526      0.526
##      Jittery         0.669      NA          0.669      0.669
##      Nervous          0.815      NA          0.815      0.815
##      Afraid           0.479      NA          0.479      0.479
##      Upset            0.633      NA          0.633      0.633
##
## Covariances:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##  G_Factor ~~
##    PAF          0.028      NA          0.028      0.028
##    NAF         -0.482      NA         -0.482     -0.482
##  PAF ~~
##    NAF          1.069      NA          1.069      1.069
##
## Thresholds:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##  Active|t1      -1.872      NA      -1.872     -1.872
##  Active|t2      -1.399      NA      -1.399     -1.399
##  Active|t3      -0.885      NA      -0.885     -0.885
##  Active|t4       0.488      NA       0.488      0.488
##  Ashamed|t1     -0.635      NA     -0.635     -0.635
##  Ashamed|t2      0.074      NA      0.074      0.074
##  Ashamed|t3      0.814      NA      0.814      0.814
##  Ashamed|t4      2.016      NA      2.016      2.016
##  Attentive|t1   -1.904      NA     -1.904     -1.904
##  Attentive|t2   -1.399      NA     -1.399     -1.399
##  Attentive|t3   -0.829      NA     -0.829     -0.829
##  Attentive|t4    0.732      NA      0.732      0.732
##  Distressed|t1  -1.090      NA     -1.090     -1.090
##  Distressed|t2  -0.488      NA     -0.488     -0.488
##  Distressed|t3   0.030      NA      0.030      0.030
##  Distressed|t4   1.141      NA      1.141      1.141
##  Determined|t1  -1.939      NA     -1.939     -1.939
##  Determined|t2  -1.303      NA     -1.303     -1.303
##  Determined|t3  -0.622      NA     -0.622     -0.622
##  Determined|t4   0.662      NA      0.662      0.662
##  Guilty|t1      -0.602      NA     -0.602     -0.602
##  Guilty|t2       0.008      NA      0.008      0.008
##  Guilty|t3       0.690      NA      0.690      0.690
##  Guilty|t4       1.621      NA      1.621      1.621
##  Excited|t1     -1.939      NA     -1.939     -1.939
##  Excited|t2     -1.266      NA     -1.266     -1.266
##  Excited|t3     -0.350      NA     -0.350     -0.350
##  Excited|t4      0.740      NA      0.740      0.740
##  Irritable|t1   -1.303      NA     -1.303     -1.303
##  Irritable|t2   -0.451      NA     -0.451     -0.451
##  Irritable|t3    0.163      NA      0.163      0.163
##  Irritable|t4    1.356      NA      1.356      1.356
##  Interested|t1  -1.872      NA     -1.872     -1.872
##  Interested|t2  -1.444      NA     -1.444     -1.444
##  Interested|t3  -0.732      NA     -0.732     -0.732
##  Interested|t4   0.622      NA      0.622      0.622
##  Scared|t1      -0.877      NA     -0.877     -0.877

```

##	Scared t2	-0.163	NA		-0.163	-0.163
##	Scared t3	0.344	NA		0.344	0.344
##	Scared t4	1.184	NA		1.184	1.184
##	Proud t1	-1.544	NA		-1.544	-1.544
##	Proud t2	-0.885	NA		-0.885	-0.885
##	Proud t3	-0.140	NA		-0.140	-0.140
##	Proud t4	0.869	NA		0.869	0.869
##	Hostile t1	-0.367	NA		-0.367	-0.367
##	Hostile t2	0.275	NA		0.275	0.275
##	Hostile t3	1.090	NA		1.090	1.090
##	Hostile t4	1.976	NA		1.976	1.976
##	Alert t1	-1.399	NA		-1.399	-1.399
##	Alert t2	-0.943	NA		-0.943	-0.943
##	Alert t3	-0.235	NA		-0.235	-0.235
##	Alert t4	0.987	NA		0.987	0.987
##	Jittery t1	-1.329	NA		-1.329	-1.329
##	Jittery t2	-0.635	NA		-0.635	-0.635
##	Jittery t3	-0.052	NA		-0.052	-0.052
##	Jittery t4	0.960	NA		0.960	0.960
##	Enthusiastic t1	-1.733	NA		-1.733	-1.733
##	Enthusiastic t2	-1.061	NA		-1.061	-1.061
##	Enthusiastic t3	-0.286	NA		-0.286	-0.286
##	Enthusiastic t4	0.837	NA		0.837	0.837
##	Nervous t1	-1.042	NA		-1.042	-1.042
##	Nervous t2	-0.367	NA		-0.367	-0.367
##	Nervous t3	0.213	NA		0.213	0.213
##	Nervous t4	1.195	NA		1.195	1.195
##	Strong t1	-1.509	NA		-1.509	-1.509
##	Strong t2	-0.951	NA		-0.951	-0.951
##	Strong t3	-0.151	NA		-0.151	-0.151
##	Strong t4	0.918	NA		0.918	0.918
##	Afraid t1	-0.207	NA		-0.207	-0.207
##	Afraid t2	0.421	NA		0.421	0.421
##	Afraid t3	1.120	NA		1.120	1.120
##	Afraid t4	1.758	NA		1.758	1.758
##	Inspired t1	-1.758	NA		-1.758	-1.758
##	Inspired t2	-1.061	NA		-1.061	-1.061
##	Inspired t3	-0.190	NA		-0.190	-0.190
##	Inspired t4	0.747	NA		0.747	0.747
##	Upset t1	-0.877	NA		-0.877	-0.877
##	Upset t2	-0.247	NA		-0.247	-0.247
##	Upset t3	0.275	NA		0.275	0.275
##	Upset t4	1.241	NA		1.241	1.241
##						
##	Variances:					
##		Estimate	Std.Err	z-value	P(> z )	Std.lv Std.all
##	.Active	0.458				0.458 0.458
##	.Ashamed	0.727				0.727 0.727
##	.Attentive	0.466				0.466 0.466
##	.Distressed	0.379				0.379 0.379
##	.Determined	0.381				0.381 0.381
##	.Guilty	0.528				0.528 0.528
##	.Excited	0.319				0.319 0.319
##	.Irritable	0.459				0.459 0.459

##	.Interested	0.358	0.358	0.358
##	.Scared	0.390	0.390	0.390
##	.Proud	0.403	0.403	0.403
##	.Hostile	0.664	0.664	0.664
##	.Alert	0.719	0.719	0.719
##	.Jittery	0.510	0.510	0.510
##	.Enthusiastic	0.295	0.295	0.295
##	.Nervous	0.257	0.257	0.257
##	.Strong	0.471	0.471	0.471
##	.Afraid	0.455	0.455	0.455
##	.Inspired	0.478	0.478	0.478
##	.Upset	0.385	0.385	0.385
##	G_Factor	1.000	1.000	1.000
##	PAf	1.000	1.000	1.000
##	NAf	1.000	1.000	1.000

```
semTools::compRelSEM(fit_bifactor_oblique)
```

##	G_Factor	PAf	NAf
##	0.133	0.234	0.667

### 3.13 Better model plot

```
#png("Figure9.png", height = 8, width = 12, units = 'in', res = 300)

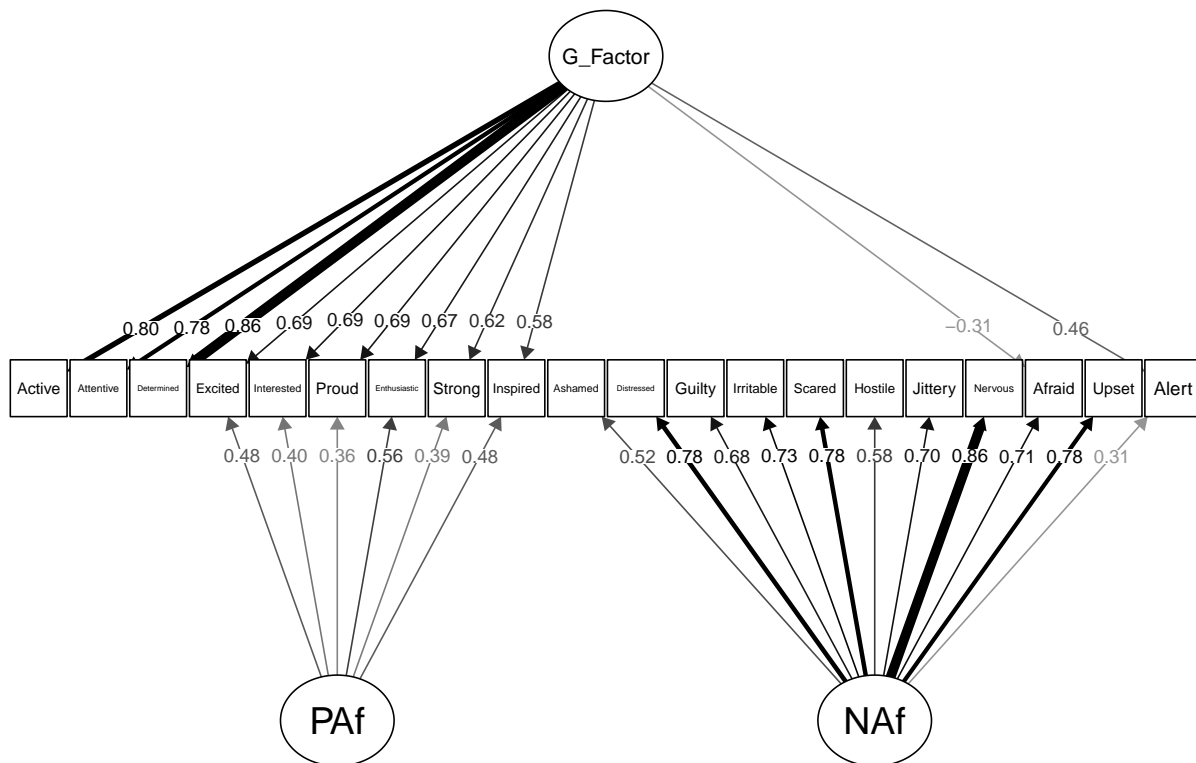
semPaths(
  fit_bifactor_constrained,
  what = "std",
  whatLabels = "est",
  edge.color="black",

  bifactor = "G_Factor",

  layout = "tree2",
  residuals = FALSE,
  intercepts = FALSE,
  thresholds = FALSE,

  edge.label.cex = 0.7,
  sizeMan = 5,
  sizeLat = 10,
  sizeLat2=8,
  edge.label.position=0.85,

  style = "lisrel",
  nCharNodes = 0,
  mar = c(2, 1, 4, 1)
)
```



```
#dev.off()
```

### 3.14 Study 2 Correlations

```
# Extract factor scores
cfa_scores <- as.data.frame(lavPredict(fit_bifactor_constrained))

# PCA scores
pca_scores <- as.data.frame(pca_results_psych$scores)

# Combine scores
all_scores <- cbind(cfa_scores, pca_scores)

# Correlation Matrix Analysis
MVN_scores <- MVN::mvn(all_scores, univariate_test = "SW")
MVN_scores$univariate_normality
```

##	Test Variable	Statistic	p.value	Normality
## 1	Shapiro-Wilk G_Factor	0.984	<0.001	Not normal
## 2	Shapiro-Wilk PAF	0.990	0.002	Not normal
## 3	Shapiro-Wilk NAF	0.997	0.544	Normal
## 4	Shapiro-Wilk RC1	0.946	<0.001	Not normal
## 5	Shapiro-Wilk RC2	0.989	0.002	Not normal

```
# Simple correlation matrix
```

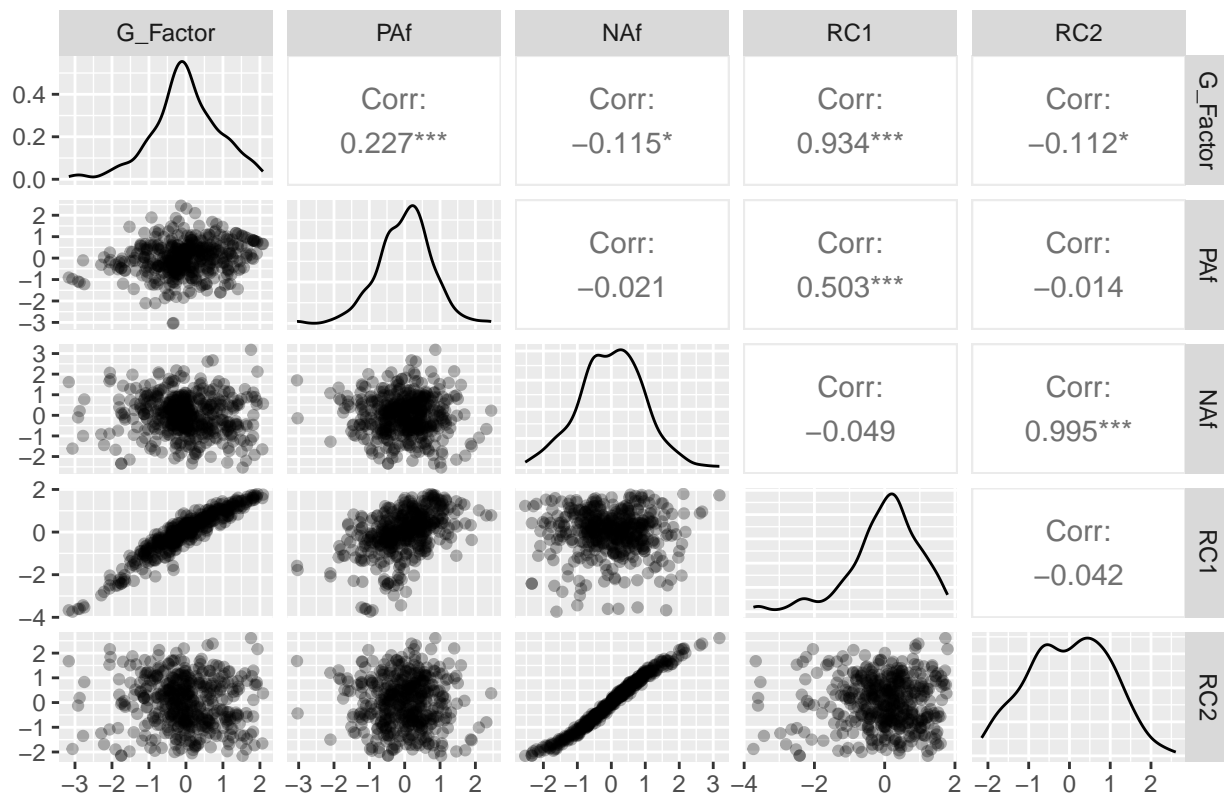
```
correlation_matrix <- cor(all_scores, method = "spearman")  
correlation_matrix_rounded <- round(correlation_matrix, 2)  
print(correlation_matrix_rounded)
```

```
##           G_Factor  PAF  NAF  RC1  RC2  
## G_Factor      1.00  0.23 -0.11  0.93 -0.11  
## PAF           0.23  1.00 -0.02  0.50 -0.01  
## NAF          -0.11 -0.02  1.00 -0.05  0.99  
## RC1           0.93  0.50 -0.05  1.00 -0.04  
## RC2          -0.11 -0.01  0.99 -0.04  1.00
```

```
# Visual visualization with GGally
```

```
ggpairs_plot <- ggpairs(  
  all_scores,  
  title = "",  
  upper = list(continuous = wrap("cor", method = "spearman", size = 4)),  
  lower = list(continuous = wrap("points", alpha = 0.3))  
)  
  
print(ggpairs_plot)
```

```
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates  
## Warning in cor.test.default(x, y, method = method): Impossível calcular o valor  
## exato de p com empates
```



```
#ggsave("Figure10.png", plot = ggpairs_plot, bg = "white", width = 10,
#       height = 6, dpi = 300)
```

### 3.15 Bifactor model with specific factors covarying vs. previous bifactor model

```
bifactor_model_syntax <- '
# General Factor (G) - All items loading on a single global dimension
G_Factor =~ Active + Ashamed + Attentive + Distressed + Determined +
  Guilty + Excited + Irritable + Interested + Scared +
  Proud + Hostile + Alert + Jittery + Enthusiastic +
  Nervous + Strong + Afraid + Inspired + Upset

# Positive Affect (PA) Specific Factor
PAf =~ Active + Attentive + Determined + Excited + Interested +
  Proud + Alert + Enthusiastic + Strong + Inspired

# Negative Affect (NA) Specific Factor
NAf =~ Ashamed + Distressed + Guilty + Irritable + Scared +
  Hostile + Jittery + Nervous + Afraid + Upset + Alert
'
```

```
#--- STEP 1: Run Orthogonal Bifactor Model ---
fit_bifactor_ortho <- cfa(bifactor_model_syntax,
  data = panas_data,
```

```

        ordered = T,
        orthogonal = T,
        estimator = "WLSMV",
        std.lv=TRUE)

#--- STEP 2: Run Oblique Bifactor Model ---
fit_bifactor_oblique <- cfa(bifactor_model_syntax,
    data = panas_data,
    ordered = T,
    # orthogonal = T, # REMOVED to allow group factor correlations
    estimator = "WLSMV",
    std.lv=TRUE)

## Warning: lavaan->lav_model_vcov():
##   Could not compute standard errors! The information matrix could not be
##   inverted. This may be a symptom that the model is not identified.

## Warning: lavaan->lav_test_satorra_bentler():
##   could not invert information matrix needed for robust test statistic

#--- STEP 3: Compare Models ---

fit_ortho_measures <- fitmeasures(fit_bifactor_ortho, c("chisq", "df", "pvalue", "cfi", "rmsea",
    "rmsea.ci.lower", "rmsea.ci.upper"))
fit_oblique_measures <- fitmeasures(fit_bifactor_oblique, c("chisq", "df", "pvalue", "cfi", "rmsea",
    "rmsea.ci.lower", "rmsea.ci.upper"))

# Print comparison
cat("--- Orthogonal Model Fit ---\n")

## --- Orthogonal Model Fit ---

print(round(fit_ortho_measures, 3))

##           chisq           df           pvalue           cfi           rmsea
##      294.436      149.000           0.000           0.994           0.046
## rmsea.ci.lower rmsea.ci.upper
##           0.038           0.054

cat("\n--- Oblique Model Fit ---\n")

##
## --- Oblique Model Fit ---

print(round(fit_oblique_measures, 3))

##           chisq           df           pvalue           cfi           rmsea
##      291.546      146.000           0.000           0.994           0.047
## rmsea.ci.lower rmsea.ci.upper
##           0.039           0.055

```

```
cat("\n--- Oblique Model Summary (Check AP~~AN Covariance) ---\n")
```

```
##
```

```
## --- Oblique Model Summary (Check AP~~AN Covariance) ---
```

```
summary(fit_bifactor_oblique, standardized = TRUE, fit.measures = TRUE)
```

```
## lavaan 0.6-20 ended normally after 61 iterations
```

```
##
```

```
## Estimator DWLS
```

```
## Optimization method NLMINB
```

```
## Number of model parameters 124
```

```
##
```

```
## Number of observations 457
```

```
##
```

```
## Model Test User Model:
```

```
## Standard Scaled
```

```
## Test Statistic 291.546 NA
```

```
## Degrees of freedom 146 146
```

```
## P-value (Chi-square) 0.000 NA
```

```
## Scaling correction factor NA
```

```
## Shift parameter NA
```

```
##
```

```
##
```

```
## Model Test Baseline Model:
```

```
##
```

```
## Test statistic 26632.140 8829.609
```

```
## Degrees of freedom 190 190
```

```
## P-value 0.000 0.000
```

```
## Scaling correction factor 3.061
```

```
##
```

```
## User Model versus Baseline Model:
```

```
##
```

```
## Comparative Fit Index (CFI) 0.994 NA
```

```
## Tucker-Lewis Index (TLI) 0.993 NA
```

```
##
```

```
## Robust Comparative Fit Index (CFI) NA
```

```
## Robust Tucker-Lewis Index (TLI) NA
```

```
##
```

```
## Root Mean Square Error of Approximation:
```

```
##
```

```
## RMSEA 0.047 NA
```

```
## 90 Percent confidence interval - lower 0.039 NA
```

```
## 90 Percent confidence interval - upper 0.055 NA
```

```
## P-value H_0: RMSEA <= 0.050 0.745 NA
```

```
## P-value H_0: RMSEA >= 0.080 0.000 NA
```

```
##
```

```
## Robust RMSEA NA
```

```
## 90 Percent confidence interval - lower NA
```

```
## 90 Percent confidence interval - upper NA
```

```
## P-value H_0: Robust RMSEA <= 0.050 NA
```

```
## P-value H_0: Robust RMSEA >= 0.080 NA
```



```

##
## Standardized Root Mean Square Residual:
##
##   SRMR                      0.048      0.048
##
## Parameter Estimates:
##
##   Parameterization          Delta
##   Standard errors          Robust.sem
##   Information              Expected
##   Information saturated (h1) model  Unstructured
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## G_Factor =~
##   Active           0.787      NA          0.787   0.787
##   Ashamed          -0.132      NA        -0.132  -0.132
##   Attentive         0.869      NA          0.869   0.869
##   Distressed        -0.223      NA        -0.223  -0.223
##   Determined         0.806      NA          0.806   0.806
##   Guilty            -0.247      NA        -0.247  -0.247
##   Excited           0.659      NA          0.659   0.659
##   Irritable         -0.005      NA        -0.005  -0.005
##   Interested         0.671      NA          0.671   0.671
##   Scared            -0.183      NA        -0.183  -0.183
##   Proud             0.652      NA          0.652   0.652
##   Hostile           -0.083      NA        -0.083  -0.083
##   Alert             0.412      NA          0.412   0.412
##   Jittery           -0.034      NA        -0.034  -0.034
##   Enthusiastic       0.634      NA          0.634   0.634
##   Nervous           -0.047      NA        -0.047  -0.047
##   Strong            0.583      NA          0.583   0.583
##   Afraid            -0.380      NA        -0.380  -0.380
##   Inspired           0.539      NA          0.539   0.539
##   Upset             -0.226      NA        -0.226  -0.226
## PAf =~
##   Active            0.157      NA          0.157   0.157
##   Attentive         -0.016      NA        -0.016  -0.016
##   Determined         0.241      NA          0.241   0.241
##   Excited           0.593      NA          0.593   0.593
##   Interested         0.502      NA          0.502   0.502
##   Proud             0.501      NA          0.501   0.501
##   Alert             0.163      NA          0.163   0.163
##   Enthusiastic       0.666      NA          0.666   0.666
##   Strong            0.510      NA          0.510   0.510
##   Inspired           0.587      NA          0.587   0.587
## NAf =~
##   Ashamed           0.518      NA          0.518   0.518
##   Distressed         0.777      NA          0.777   0.777
##   Guilty            0.667      NA          0.667   0.667
##   Irritable          0.742      NA          0.742   0.742
##   Scared            0.775      NA          0.775   0.775
##   Hostile           0.582      NA          0.582   0.582
##   Jittery           0.705      NA          0.705   0.705

```

```

##      Nervous      0.868      NA      0.868      0.868
##      Afraid      0.686      NA      0.686      0.686
##      Upset      0.773      NA      0.773      0.773
##      Alert      0.357      NA      0.357      0.357
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      G_Factor ~~
##      PAF      -0.104      NA      -0.104      -0.104
##      NAF      0.088      NA      0.088      0.088
##      PAF ~~
##      NAF      -0.077      NA      -0.077      -0.077
##
## Thresholds:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      Active|t1      -1.872      NA      -1.872      -1.872
##      Active|t2      -1.399      NA      -1.399      -1.399
##      Active|t3      -0.885      NA      -0.885      -0.885
##      Active|t4       0.488      NA       0.488       0.488
##      Ashamed|t1     -0.635      NA     -0.635     -0.635
##      Ashamed|t2       0.074      NA       0.074       0.074
##      Ashamed|t3       0.814      NA       0.814       0.814
##      Ashamed|t4       2.016      NA       2.016       2.016
##      Attentive|t1    -1.904      NA     -1.904     -1.904
##      Attentive|t2    -1.399      NA     -1.399     -1.399
##      Attentive|t3    -0.829      NA     -0.829     -0.829
##      Attentive|t4       0.732      NA       0.732       0.732
##      Distressed|t1   -1.090      NA     -1.090     -1.090
##      Distressed|t2   -0.488      NA     -0.488     -0.488
##      Distressed|t3     0.030      NA      0.030      0.030
##      Distressed|t4     1.141      NA      1.141      1.141
##      Determined|t1   -1.939      NA     -1.939     -1.939
##      Determined|t2   -1.303      NA     -1.303     -1.303
##      Determined|t3   -0.622      NA     -0.622     -0.622
##      Determined|t4     0.662      NA      0.662      0.662
##      Guilty|t1      -0.602      NA     -0.602     -0.602
##      Guilty|t2       0.008      NA      0.008      0.008
##      Guilty|t3       0.690      NA      0.690      0.690
##      Guilty|t4       1.621      NA      1.621      1.621
##      Excited|t1      -1.939      NA     -1.939     -1.939
##      Excited|t2      -1.266      NA     -1.266     -1.266
##      Excited|t3      -0.350      NA     -0.350     -0.350
##      Excited|t4       0.740      NA      0.740      0.740
##      Irritable|t1    -1.303      NA     -1.303     -1.303
##      Irritable|t2    -0.451      NA     -0.451     -0.451
##      Irritable|t3     0.163      NA      0.163      0.163
##      Irritable|t4     1.356      NA      1.356      1.356
##      Interested|t1   -1.872      NA     -1.872     -1.872
##      Interested|t2   -1.444      NA     -1.444     -1.444
##      Interested|t3   -0.732      NA     -0.732     -0.732
##      Interested|t4     0.622      NA      0.622      0.622
##      Scared|t1      -0.877      NA     -0.877     -0.877
##      Scared|t2      -0.163      NA     -0.163     -0.163
##      Scared|t3       0.344      NA      0.344      0.344

```

##	Scared t4	1.184	NA		1.184	1.184
##	Proud t1	-1.544	NA		-1.544	-1.544
##	Proud t2	-0.885	NA		-0.885	-0.885
##	Proud t3	-0.140	NA		-0.140	-0.140
##	Proud t4	0.869	NA		0.869	0.869
##	Hostile t1	-0.367	NA		-0.367	-0.367
##	Hostile t2	0.275	NA		0.275	0.275
##	Hostile t3	1.090	NA		1.090	1.090
##	Hostile t4	1.976	NA		1.976	1.976
##	Alert t1	-1.399	NA		-1.399	-1.399
##	Alert t2	-0.943	NA		-0.943	-0.943
##	Alert t3	-0.235	NA		-0.235	-0.235
##	Alert t4	0.987	NA		0.987	0.987
##	Jittery t1	-1.329	NA		-1.329	-1.329
##	Jittery t2	-0.635	NA		-0.635	-0.635
##	Jittery t3	-0.052	NA		-0.052	-0.052
##	Jittery t4	0.960	NA		0.960	0.960
##	Enthusiastic t1	-1.733	NA		-1.733	-1.733
##	Enthusiastic t2	-1.061	NA		-1.061	-1.061
##	Enthusiastic t3	-0.286	NA		-0.286	-0.286
##	Enthusiastic t4	0.837	NA		0.837	0.837
##	Nervous t1	-1.042	NA		-1.042	-1.042
##	Nervous t2	-0.367	NA		-0.367	-0.367
##	Nervous t3	0.213	NA		0.213	0.213
##	Nervous t4	1.195	NA		1.195	1.195
##	Strong t1	-1.509	NA		-1.509	-1.509
##	Strong t2	-0.951	NA		-0.951	-0.951
##	Strong t3	-0.151	NA		-0.151	-0.151
##	Strong t4	0.918	NA		0.918	0.918
##	Afraid t1	-0.207	NA		-0.207	-0.207
##	Afraid t2	0.421	NA		0.421	0.421
##	Afraid t3	1.120	NA		1.120	1.120
##	Afraid t4	1.758	NA		1.758	1.758
##	Inspired t1	-1.758	NA		-1.758	-1.758
##	Inspired t2	-1.061	NA		-1.061	-1.061
##	Inspired t3	-0.190	NA		-0.190	-0.190
##	Inspired t4	0.747	NA		0.747	0.747
##	Upset t1	-0.877	NA		-0.877	-0.877
##	Upset t2	-0.247	NA		-0.247	-0.247
##	Upset t3	0.275	NA		0.275	0.275
##	Upset t4	1.241	NA		1.241	1.241
##						
##	Variances:					
##		Estimate	Std.Err	z-value	P(> z )	Std.lv Std.all
##	.Active	0.381				0.381 0.381
##	.Ashamed	0.726				0.726 0.726
##	.Attentive	0.242				0.242 0.242
##	.Distressed	0.377				0.377 0.377
##	.Determined	0.333				0.333 0.333
##	.Guilty	0.523				0.523 0.523
##	.Excited	0.295				0.295 0.295
##	.Irritable	0.449				0.449 0.449
##	.Interested	0.368				0.368 0.368
##	.Scared	0.391				0.391 0.391

##	.Proud	0.391	0.391	0.391
##	.Hostile	0.662	0.662	0.662
##	.Alert	0.674	0.674	0.674
##	.Jittery	0.506	0.506	0.506
##	.Enthusiastic	0.242	0.242	0.242
##	.Nervous	0.251	0.251	0.251
##	.Strong	0.462	0.462	0.462
##	.Afraid	0.431	0.431	0.431
##	.Inspired	0.431	0.431	0.431
##	.Upset	0.382	0.382	0.382
##	G_Factor	1.000	1.000	1.000
##	PAf	1.000	1.000	1.000
##	NAf	1.000	1.000	1.000

#### sessionInfo()

```
## R version 4.5.0 (2025-04-11 ucrt)
## Platform: x86_64-w64-mingw32/x64
## Running under: Windows 11 x64 (build 26100)
##
## Matrix products: default
##   LAPACK version 3.12.1
##
## locale:
## [1] LC_COLLATE=Portuguese_Brazil.utf8  LC_CTYPE=Portuguese_Brazil.utf8
## [3] LC_MONETARY=Portuguese_Brazil.utf8 LC_NUMERIC=C
## [5] LC_TIME=Portuguese_Brazil.utf8
##
## time zone: America/Sao_Paulo
## tzcode source: internal
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods    base
##
## other attached packages:
## [1] DiagrammeRsvg_0.1      magick_2.9.0           DiagrammeR_1.0.11
## [4] plotly_4.11.0          semPlot_1.1.7          GGally_2.4.0
## [7] ggrepel_0.9.6          patchwork_1.3.2        ggplot2_4.0.1
## [10] EGAnet_2.3.0           cSEM_0.6.1             seminr_2.3.7
## [13] semTools_0.5-7         lavaan_0.6-20          MVN_6.2
## [16] GPArotation_2025.3-1   EFA.dimensions_0.1.8.4 psych_2.5.3
## [19] tidytext_0.4.3         stringr_1.6.0          stringi_1.8.7
## [22] janitor_2.2.1          tidyr_1.3.1            dplyr_1.1.4
## [25] readxl_1.4.5           readr_2.1.6            pacman_0.5.1
##
## loaded via a namespace (and not attached):
## [1] matrixStats_1.5.0      lubridate_1.9.4        httr_1.4.7
## [4] webshot_0.5.5          RColorBrewer_1.1-3     tools_4.5.0
## [7] backports_1.5.0        utf8_1.2.6            R6_2.6.1
## [10] vegan_2.7-2            lazyeval_0.2.2         mgcv_1.9-4
## [13] noritest_1.0-4         jomo_2.7-6             permute_0.9-8
## [16] withr_3.0.2            gridExtra_2.3          fdrtool_1.2.18
## [19] progressr_0.18.0       polycor_0.8-1          qgraph_1.9.8
## [22] textshaping_1.0.4      cli_3.6.5              sandwich_3.1-1
```

## [25]	labeling_0.4.3	mvtnorm_1.3-3	S7_0.2.1
## [28]	pbapply_1.7-4	pbivnorm_0.6.0	systemfonts_1.3.1
## [31]	foreign_0.8-90	R.utils_2.13.0	parallelly_1.44.0
## [34]	sessioninfo_1.2.3	lisrelToR_0.3	rstudioapi_0.17.1
## [37]	visNetwork_2.1.4	generics_0.1.4	shape_1.4.6.1
## [40]	gtools_3.9.5	vroom_1.6.6	car_3.1-3
## [43]	zip_2.3.3	OpenMx_2.22.10	Matrix_1.7-3
## [46]	clipr_0.8.0	abind_1.4-8	R.methodsS3_1.8.2
## [49]	lifecycle_1.0.4	multcomp_1.4-29	yaml_2.3.10
## [52]	snakecase_0.11.1	carData_3.0-5	grid_4.5.0
## [55]	promises_1.3.2	crayon_1.5.3	mitml_0.4-5
## [58]	lattice_0.22-7	chromote_0.5.1	pillar_1.11.1
## [61]	knitr_1.50	boot_1.3-32	estimability_1.5.1
## [64]	corpcor_1.6.10	future.apply_1.20.0	admisc_0.39
## [67]	codetools_0.2-20	pan_1.9	glue_1.8.0
## [70]	beepR_2.0	V8_8.0.1	data.table_1.17.0
## [73]	vctrs_0.6.5	png_0.1-8	Rdpack_2.6.4
## [76]	testthat_3.3.0	cellranger_1.1.0	gtable_0.3.6
## [79]	xfun_0.52	openxlsx_4.2.8.1	rbibutils_2.3
## [82]	coda_0.19-4.1	reformulas_0.4.2	survival_3.8-3
## [85]	audio_0.1-11	iterators_1.0.14	TH.data_1.1-5
## [88]	nlme_3.1-168	bit64_4.6.0-1	mi_1.2
## [91]	SnowballC_0.7.1	Deriv_4.2.0	rpart_4.1.24
## [94]	colorspace_2.1-1	Hmisc_5.2-3	nnet_7.3-20
## [97]	mnormt_2.1.1	tidyselect_1.2.1	processx_3.8.6
## [100]	emmeans_2.0.0	moments_0.14.1	bit_4.6.0
## [103]	compiler_4.5.0	curl_7.0.0	glmnet_4.1-8
## [106]	htmlTable_2.4.3	mice_3.17.0	checkmate_2.3.2
## [109]	scales_1.4.0	quadprog_1.5-8	sem_3.1-16
## [112]	digest_0.6.38	minqa_1.2.8	rmarkdown_2.30
## [115]	htmltools_0.5.8.1	pkgconfig_2.0.3	jpeg_0.1-11
## [118]	base64enc_0.1-3	SimDesign_2.21	lme4_1.1-37
## [121]	fastmap_1.2.0	rlang_1.1.6	htmlwidgets_1.6.4
## [124]	farver_2.1.2	zoo_1.8-14	jsonlite_2.0.0
## [127]	energy_1.7-12	dcurver_0.9.3	tokenizers_0.3.0
## [130]	R.oo_1.27.1	magrittr_2.0.3	Formula_1.2-5
## [133]	Rcpp_1.1.0	viridis_0.6.5	rockchalk_1.8.157
## [136]	brio_1.1.5	MASS_7.3-65	plyr_1.8.9
## [139]	ggstats_0.11.0	parallel_4.5.0	listenv_0.10.0
## [142]	kutils_1.73	splines_4.5.0	hms_1.1.4
## [145]	ps_1.9.1	igraph_2.2.1	reshape2_1.4.4
## [148]	stats4_4.5.0	XML_3.99-0.20	evaluate_1.0.5
## [151]	RcppParallel_5.1.11-1	nloptr_2.2.1	tzdb_0.5.0
## [154]	foreach_1.5.2	webshot2_0.1.2	purrr_1.0.4
## [157]	future_1.68.0	mirt_1.45.1	broom_1.0.10
## [160]	xtable_1.8-4	janeaustenr_1.0.0	later_1.4.2
## [163]	glasso_1.11	viridisLite_0.4.2	ragg_1.5.0
## [166]	gsl_2.1-9	arm_1.14-4	tibble_3.2.1
## [169]	websocket_1.4.4	cluster_2.1.8.1	timechange_0.3.0
## [172]	globals_0.18.0		