

Colombian trans wellbeing

Code and analyses

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Description

This document contains all code, and step by step explanations for all analyses, figures and tables (including supplementary figures and tables) for:

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Data are available on the Open Science Framework (OSF): <https://doi.org/10.XXXXXX/OSF.IO/XXXXX>.

The analyses were designed by Maria Fernanda Reyes-Rodríguez and Juan David Leongómez. This document and its underlying code were created in R Markdown by Juan David Leongómez using R and L^AT_EX, ensuring full reproducibility.

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1 Preliminaries

1.1 Load packages

This file was created using `knitr` (Xie, 2014), mostly using `tidyverse` (Wickham et al., 2019) syntax. As such, data wrangling was mainly done using packages such as `dplyr` (Wickham et al., 2023), and most figures were created or modified using `ggplot2` (Wickham, 2016). Tables were created using `knitr::kable` and `kableExtra` (Zhu, 2021).

Multi-model inference and model averaging was achieved using `MuMIn` (Bartoń, 2024), and model assumptions were performed using `performance` (Lüdtke et al., 2021).

All packages used in this file can be directly installed from the Comprehensive R Archive Network ([CRAN](https://cran.r-project.org/)). For a complete list of packages used to create this file, and their versions, see section 6, at the end of the document.

```
library(ltm)
library(psych) # For statistical functions (e.g., Cronbach's alpha)
library(MuMIn) # For model selection and averaging
library(performance) # For model performance metrics
library(readr) # For reading data files
library(scales) # For percent formatting
library(knitr)
library(kableExtra)
library(car)
library(tidyverse) # For data manipulation and piping
library(ggpubr)
library(gtsummary)
library(Hmisc)
```

1.2 Custom functions

1.2.1 pval.lev and pval.stars

These functions take p-values and formats them, either in L^AT_EX and highlighting significant p-values in bold and representing all in an appropriate level, or as stars.

```
# Function to format p-values for LaTeX output, highlighting significant values in bold
pval.lev <- function(pvals) {
  ifelse(pvals < 0.0001, "\\textbf{< 0.0001}", # Highlight very small p-values
  ifelse(pvals < 0.001, "\\textbf{< 0.001}", # Bold p-values < 0.001
  ifelse(pvals < 0.05, paste0("\\textbf{", round(pvals, 4), "}"), # Bold p-values < 0.05
  round(pvals, 2) # Round non-significant values to two decimal places
  )
  )
}

# Function to add significance stars based on p-value thresholds
pval.stars <- function(pvals) {
  ifelse(pvals < 0.0001, "****", # Four stars for p < 0.0001
  ifelse(pvals < 0.001, "***", # Three stars for p < 0.001
  ifelse(pvals < 0.01, "**", # Two stars for p < 0.01
  ifelse(pvals < 0.05, "*", NA) # One star for p < 0.05, NA otherwise
  )
  )
}
```

1.2.2 corr.stars

This function creates a correlation matrix, and displays significance (function `corr.stars` modified from <http://myowelt.blogspot.com/2008/04/beautiful-correlation-tables-in-r.html>).

```
# Function to create a correlation matrix with significance levels in LaTeX format
corr.stars <- function(x) {
  require(Hmisc) # Load Hmisc package for correlation and p-value calculations
  x <- as.matrix(x) # Ensure input is a matrix
  R <- rcorr(x, type = "spearman")$r # Compute correlation coefficients
  p <- rcorr(x, type = "spearman")$P # Extract p-values for significance testing
  # Define symbols for significance levels, using LaTeX formatting for bold and stars
  mystars <- ifelse(p < .001, paste0("\\textbf{", round(R, 2), "***}"), # p < 0.001
  ifelse(p < .01, paste0("\\textbf{", round(R, 2), "**}"), # p < 0.01
  ifelse(p < .05, paste0("\\textbf{", round(R, 2), "*}"), # p < 0.05
  ifelse(p < .10, paste0(round(R, 2), "$^{\\dagger}$"), # p < 0.10 (trend level)
  format(round(R, 2), nsmall = 2) # Format non-significant values with two decimals
  )
  )
  )
  # Construct a new matrix with correlation values and significance symbols
  Rnew <- matrix(mystars, ncol = ncol(x))
  # Ensure diagonal values remain the original correlation values (without significance symbols)
  diag(Rnew) <- paste(diag(R), " ", sep = "")
  # Assign row and column names for the formatted matrix
  rownames(Rnew) <- colnames(x)
  colnames(Rnew) <- paste(colnames(x), "", sep = "")
  # Remove the upper triangle of the matrix (including the diagonal) for a clean presentation
  Rnew <- as.matrix(Rnew)
```

```

Rnew[upper.tri(Rnew, diag = TRUE)] <- ""
# Convert to a data frame for better handling and remove the last empty column
Rnew <- as.data.frame(Rnew)
Rnew <- cbind(Rnew[1:length(Rnew) - 1])
return(Rnew) # Return formatted correlation table
}

```

1.2.3 dredge.plot

This function generates a model selection plot from a `MuMIn::dredge()` model selection table. It visualizes the top 100 models, showing which terms are included in each model and their relative importance based on Akaike weights. It also dynamically creates a caption summarizing the number of fitted models, which can be used in `fig.cap`.

```

dredge.plot <- function(mod.sel.table) {
  # Ensure the input is a dredge object
  if (!inherits(mod.sel.table, "model.selection")) {
    stop("Input must be a MuMIn::dredge() model selection table.")
  }

  # Generate the caption dynamically
  caption <- paste0(
    "Model selection plot. Each row represents one of the top 100 models ",
    "(ranked by $AICc$) out of ", formatC(dim(mod.sel.table)[1], big.mark = ","),
    " fitted models. Blue cells indicate included terms, with shading ",
    "intensity reflecting their Akaike weight ($w_i(AICc)$). Row height ",
    "corresponds to each model's relative support based on $w_i(AICc)$."
  )

  # Generate the plot
  plot_object <- plot(mod.sel.table[1:100, ], col = "#0D088750")

  # Return both the plot and the caption in a named list
  return(list(plot = plot_object, caption = caption))
}

```

1.2.4 avg.mod.summary

This function creates a formatted summary table for model-averaged coefficients obtained from `MuMIn::model.avg()`. It includes coefficient estimates and 95% confidence intervals, significance levels (formatted for LaTeX output), a dynamically generated caption including the dependent variable name, and a footnote specifying reference levels for categorical predictors.

```

avg.mod.summary <- function(avg_model, data) {
  # Function to extract relevant reference levels
  extract_relevant_reference_levels <- function(avg_model, data) {
    # Identify factor variables in the dataset
    factor_vars <- names(data)[sapply(data, is.factor)]
    # Get reference levels for each factor variable
    ref_levels <- sapply(factor_vars, function(var) levels(data[[var]])[1])
    # Extract model terms
    model_terms <- rownames(summary(avg_model)$coefmat.full)
    # Detect which model terms correspond to factor variables
    relevant_factors <-
      factor_vars[sapply(factor_vars,
        function(var) any(grepl(paste0("^", var), model_terms)))]
    # Keep only reference levels for relevant factors
    relevant_refs <- ref_levels[names(ref_levels) %in% relevant_factors]
  }
}

```

```

# Format the output
if (length(relevant_refs) > 0) {
  paste0(
    "Reference levels: ",
    paste0(names(relevant_refs),
           " = ", relevant_refs,
           collapse = "; ")
  )
} else {
  "No factor variables in the average model"
}
}

# Compute CIs
cis <- confint(avg_model, full = TRUE) |>
  as.data.frame() |>
  mutate(across(everything(), round, 3)) |>
  unite(col = "CI", `2.5 %`:`97.5 %`, sep = " - ")

# Full average summary table
summ_table <- summary(avg_model)$coefmat.full |>
  as.data.frame() |>
  bind_cols(cis) |>
  rownames_to_column(var = "term") |>
  mutate(term = term |>
    str_replace_all("Gender", "Gender: ") |>
    str_replace_all("Housing", "Housing: ") |>
    str_replace_all("Ethnicity", "Ethnicity: ") |>
    str_replace_all("Education", "Education: ") |>
    str_replace_all("_", " ") |>
    select(term, Estimate, CI, `z value`, `Pr(>|z|)`) |>
    mutate(`Pr(>|z|)` = pval.lev(`Pr(>|z|)`) |>
    arrange(term)

kable_tab <- kable(
  summ_table,
  digits = 3,
  booktabs = TRUE,
  linesep = "",
  align = c("l", rep("c", 4)),
  caption = paste0(
    "Coefficient estimates for the ",
    as.character(avg_model$formula)[2] |>
    str_replace("_", " "),
    " model."
  ),
  col.names = c("Term", "$B$", "$95 %% CIs$", "$z$", "$p$"),
  escape = FALSE
) |>
kable_styling(latex_options = "HOLD_position") |>
footnote(
  general = paste0(
    "This table includes estimates based on a full model average. ",
    "The full model average ensures that all variables are included in every model, ",
    "with coefficients set to zero when absent. As a consequence, it acts as a shrinkage ",

```

```

    "estimator, making estimates more conservative. ",
    "$B$ represents unstandardized model coefficients. ",
    extract_relevant_reference_levels(avg_model, data), # Now using the internal function
    ". Significant effects are in bold."
  ),
  threeparttable = TRUE,
  footnote_as_chunk = TRUE,
  escape = FALSE
)

# Return all intermediate objects
return(list(table = kable_tab,
            coefficients = summ_table,
            reference_levels = extract_relevant_reference_levels(avg_model, data)))
}

```

1.2.5 avg.mod.plot

This function visualizes model-averaged estimates from `MuMIn::model.avg()`, displaying point estimates with 95% confidence intervals, predictor importance (mapped to point size and colour), and a dynamically generated annotation for the number of averaged model.

```

avg.mod.plot <- function(avg_mod) {
  # Extract model summary and transform into a tidy format
  x <- summary(avg_mod)$coefmat.full |>
  as_tibble(rownames = "key") |> # Convert row names to a "key" column
  bind_cols(
    confint(avg_mod, full = TRUE) |> as_tibble(), # Add confidence intervals
    summary(avg_mod)$coef.nmod |>
    as_tibble() |>
    pivot_longer(cols = everything(), names_to = "model", values_to = "value") # Gather number of models
  ) |>
  mutate(
    avmod = deparse(substitute(avg_mod)) |>
    factor(), # Store model name as a factor
    value = value / max(value, na.rm = TRUE), # Normalize 'value' column
    sig = pval.stars(`Pr(>|z|)` ) |>
    str_replace("\\.", "†"), # Convert p-values into significance stars
    key = key |>
    str_replace_all("Gender", "Gender: ") |>
    str_replace_all("Housing", "Housing: ") |>
    str_replace_all("Ethnicity", "Ethnicity: ") |>
    str_replace_all("Education", "Education: ") |>
    str_replace_all("_", " ")
  )

  x <- x |>
  mutate(key = factor(key, levels = as.character(unique(x$key))))

  # Get the number of averaged models
  nMods <- dim(avg_mod$msTable)[1]

  # Create the plot
  ggplot(x, aes(x = key, y = Estimate)) +
    # Add horizontal reference line at zero
    geom_hline(yintercept = 0, color = "grey") +
    # Add points sized and colored by importance

```

```

geom_point(aes(size = value, color = value), alpha = 0.5) +
# Add error bars (confidence intervals)
geom_errorbar(aes(ymin = `2.5 %`, ymax = `97.5 %`),
  colour = "black", width = 0.1
) +
# Add additional points for emphasis
geom_point(size = 1) +
# Apply theme and labels
theme_bw() +
labs(x = NULL, y = "Estimate") +
theme(axis.text.x = element_text(angle = 60, hjust = 1)) +
# Scale for importance (value) size
scale_size_continuous(
  range = c(2, 8),
  breaks = seq(0, 1, by = 0.2)
) +
# Legends for size and color
guides(
  size = guide_legend(title = "Importance"),
  color = guide_legend(title = "Importance")
) +
# Ensure x-axis labels remain in the correct order
scale_x_discrete(
  labels = levels(x$key),
  expand = c(0, 0.5)
) +
# Use plasma color scale, reversed so darker colors represent higher values
scale_colour_viridis_c(
  option = "plasma", direction = -1,
  breaks = seq(0, 1, by = 0.2)
) +
# Add significance labels next to points
geom_text(aes(label = sig), y = x$`97.5 %`, vjust = -0.4) +
# Add annotation indicating the number of averaged models
geom_text(
  aes(
    x = Inf, y = Inf,
    label = paste("Models averaged = ", nMods)
  ),
  # fontface = "italic",
  size = 3,
  hjust = 1.1,
  vjust = 1.8,
  inherit.aes = FALSE
)
}

```

1.3 Load data

Load raw CSV data

```
data_RAW <- read_csv("data/data.csv")
```

1.3.1 Define PANAS Subscales (Positive & Negative Affect)

The Positive and Negative Affect Schedule (PANAS) is a widely used self-report questionnaire that measures two independent dimensions of affect:

- Positive Affect (PA): Reflects the extent to which a person feels enthusiastic, active, and alert.
- Negative Affect (NA): Represents distress and unpleasurable engagement, including emotions such as fear, anger, and nervousness.

The following lists define the PANAS subscales based on their respective items.

```
# List of PANAS Positive Affect (PANAS_P) items
PANAS_P <- c(
  "PANASB_1", "PANASB_3", "PANASB_5", "PANASB_9",
  "PANASB_10", "PANASB_12", "PANASB_14", "PANASB_16",
  "PANASB_17", "PANASB_19"
)

# List of PANAS Negative Affect (PANAS_N) items
PANAS_N <- c(
  "PANASB_2", "PANASB_4", "PANASB_6", "PANASB_7",
  "PANASB_8", "PANASB_11", "PANASB_13", "PANASB_15",
  "PANASB_18", "PANASB_20"
)
```

1.4 Internal consistency

1.4.1 Calculate Cronbach's Alpha for Different Scales

To measure the internal consistency of these tests, we used standardized Cronbach's alpha (α or Tau-equivalent reliability: ρ_T) coefficients, using the function `cronbach.alpha` from the package `ltm` (Rizopoulos, 2006).

```
# Compute Cronbach's alpha for the Self-Efficacy (EAG) scale
alpha_EAG <- data_RAW |>
  mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA (missing values)
  select(starts_with("EAG_")) |> # Select all columns starting with "EAG_"
  drop_na() |>
  cronbach.alpha(CI = TRUE, standardized = TRUE) # Compute Cronbach's alpha

# Compute Cronbach's alpha for the Life-Satisfaction (SWLS) scale
alpha_SWLS <- data_RAW |>
  mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
  select(starts_with("SWLS_")) |> # Select all columns starting with "SWLS_"
  drop_na() |>
  cronbach.alpha(CI = TRUE, standardized = TRUE)

# Compute Cronbach's alpha for the Resilience (EBR) scale
alpha_EBR <- data_RAW |>
  mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
  select(starts_with("EBR_")) |> # Select all columns starting with "EBR_"
  drop_na() |>
  cronbach.alpha(CI = TRUE, standardized = TRUE)

# Compute Cronbach's alpha for the Depression (EBD) scale (after recoding responses)
alpha_EBD <- data_RAW |>
  mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
  select(starts_with("EBD_")) |> # Select all columns starting with "EBD_"
  mutate(across(everything(), ~ ifelse(is.na(.x), NA, .x - 1))) |> # Adjust values
  drop_na() |>
  cronbach.alpha(CI = TRUE, standardized = TRUE)

# Compute Cronbach's alpha for the Social Support (MOS2) scale
alpha_MOS2 <- data_RAW |>
```



```

mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
select(starts_with("MOS2_")) |> # Select all columns starting with "MOS2_"
drop_na() |>
cronbach.alpha(CI = TRUE, standardized = TRUE)

# Compute Cronbach's alpha for PANAS Positive Affect (PANAS_P)
alpha_PANAS_P <- data_RAW |>
mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
select(all_of(PANAS_P)) |> # Select PANAS_P variables
drop_na() |>
cronbach.alpha(CI = TRUE, standardized = TRUE)

# Compute Cronbach's alpha for PANAS Negative Affect (PANAS_N)
alpha_PANAS_N <- data_RAW |>
mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
select(all_of(PANAS_N)) |> # Select PANAS_N variables
drop_na() |>
cronbach.alpha(CI = TRUE, standardized = TRUE)

# Compute Cronbach's alpha for Community Cohesion (PCPS3) scale
alpha_PCPS3 <- data_RAW |>
mutate(across(where(is.numeric), ~ na_if(., 99))) |> # Replace 99 with NA
select(starts_with("PCPS3_")) |> # Select all columns starting with "PCPS3_"
drop_na() |>
cronbach.alpha(CI = TRUE, standardized = TRUE)

```

1.4.2 Table S1. Internal consistency of measured scales

The internal consistency of the measured scales was generally strong, with Cronbach's α values ranging from 0.767 to 0.977. In particular, the Social Support (MOS2) and Self-Efficacy (EAG) scales exhibited excellent internal consistency, while the Depression (EBD) and Community Cohesion (PCPS3) scales had acceptable reliability, suggesting a slightly lower but still adequate level of internal consistency.

```

tibble(
  Scale = c(
    "Self-Efficacy$^1$",
    "Life-Satisfaction$^2$",
    "Resilience$^3$",
    "Depression$^4$",
    "Social Support$^5$",
    "PANAS Positive$^6$",
    "PANAS Negative$^6$",
    "Community Cohesion$^7$"
  ),
  p = c(
    alpha_EAG$p, alpha_SWLS$p, alpha_EBR$p, alpha_EBD$p, alpha_MOS2$p,
    alpha_PANAS_P$p, alpha_PANAS_N$p, alpha_PCPS3$p
  ),
  n = c(
    alpha_EAG$n, alpha_SWLS$n, alpha_EBR$n, alpha_EBD$n, alpha_MOS2$n,
    alpha_PANAS_P$n, alpha_PANAS_N$n, alpha_PCPS3$n
  ),
  alpha = c(
    alpha_EAG$alpha, alpha_SWLS$alpha, alpha_EBR$alpha, alpha_EBD$alpha,
    alpha_MOS2$alpha, alpha_PANAS_P$alpha, alpha_PANAS_N$alpha, alpha_PCPS3$alpha
  ),

```

```

ci2.5 = c(
  alpha_EAG$ci[1], alpha_SWLS$ci[1], alpha_EBR$ci[1], alpha_EBD$ci[1],
  alpha_MOS2$ci[1], alpha_PANAS_P$ci[1], alpha_PANAS_N$ci[1], alpha_PCPS3$ci[1]
),
ci97.5 = c(
  alpha_EAG$ci[2], alpha_SWLS$ci[2], alpha_EBR$ci[2], alpha_EBD$ci[2],
  alpha_MOS2$ci[2], alpha_PANAS_P$ci[2], alpha_PANAS_N$ci[2], alpha_PCPS3$ci[2]
)
) |>
mutate(across(starts_with("ci"), round, 3)) |>
unite(col = "CI", ci2.5:ci97.5, sep = " - ") |>
kable(
  digits = 3,
  booktabs = TRUE,
  linesep = "",
  align = c("l", rep("c", 4)),
  caption = "Internal consistency of measured scales",
  col.names = c("Variable", "Items", "$n$", "$\\alpha$", "$95\\% CI$"),
  escape = FALSE
) |>
kable_styling(latex_options = "HOLD_position") |>
footnote(
  general = "95\\\\% confidence intervals were calculated with 1,000 bootstrap samples.
  Standardized Cronbach's alpha ($\\\\alpha$) coefficients were computed.
  $^1$\\\\cite{EAG};
  $^2$\\\\cite{SWLS};
  $^3$\\\\cite{EBR};
  $^4$\\\\cite{EBD};
  $^5$\\\\cite{MOS};
  $^6$\\\\cite{PANAS};
  $^7$\\\\cite{PCPS3}.",
  threeparttable = TRUE, footnote_as_chunk = TRUE, escape = FALSE
)

```

Table S1. Internal consistency of measured scales

Variable	Items	<i>n</i>	α	95%CI
Self-Efficacy ¹	10	223	0.905	0.875 — 0.928
Life-Satisfaction ²	5	253	0.869	0.84 — 0.894
Resilience ³	4	278	0.861	0.824 — 0.892
Depression ⁴	7	223	0.767	0.71 — 0.809
Social Support ⁵	19	195	0.977	0.971 — 0.981
PANAS Positive ⁶	10	285	0.884	0.858 — 0.906
PANAS Negative ⁶	10	282	0.827	0.794 — 0.868
Community Cohesion ⁷	3	281	0.769	0.696 — 0.826

Note: 95% confidence intervals were calculated with 1,000 bootstrap samples. Standardized Cronbach's alpha (α) coefficients were computed. ¹Baessler and Schwarzer, 1996; ²Diener et al., 1985; ³Sinclair and Wallston, 2004; ⁴Andresen et al., 1994; ⁵Sherbourne and Stewart, 1991; ⁶Watson et al., 1988; ⁷Stanton et al., 2017.

2 Data Preprocessing

2.1 Renaming, recoding, and filtering

This section prepares the raw dataset (`data_RAW`) and creates a dataset (`data`) for analysis by:

- Renaming variables to meaningful labels
- Handling missing values (99 → NA)
- Recoding categorical variables into human-readable labels
- Aggregating key variables (e.g., polyconsumption, discrimination, depression)
- Filtering out ineligible cases (e.g., participants under 18)

```
data <- data_RAW |>
# Rename columns to meaningful names
rename(
  Age = SD1,
  City = SD2,
  Gender = SD3,
  Sexualorientation = SD4,
  Sex = SD5,
  Ethnicity = SD6,
  Farmer = SD7,
  Marital_Status = SD8,
  SES = SD9, # Socioeconomic Status
  Education = SD10,
  Children = SD11,
  Housing = SD12,
  Cohabitant = SD13,
  Monthly_Income = SD14,
  Income_Source = SD15,
  Employment = SD16,
  Job = SD17,
  # Disabilities and difficulties
  Hearing_Difficulties = SD18_1,
  Speaking_Difficulties = SD18_2,
  Seeing_Difficulties = SD18_3,
  Moving_Difficulties = SD18_4,
  Grabing_Difficulties = SD18_5,
  Understanding_Difficulties = SD18_6,
  Interacting_Difficulties = SD18_7,
  # Lifetime Prevalence (LP) of substance use
  LP_Alcohol = SD19_1_A,
  LP_Cigarette = SD19_2_A,
  LP_Cannabis = SD19_3_A,
  LP_Cocaine = SD19_4_A,
  LP_Basuco = SD19_5_A,
  LP_Inhalant = SD19_6_A,
  LP_Ecstasy = SD19_7_A,
  LP_Psilocybin = SD19_8_A,
  LP_LSD = SD19_9_A,
  LP_Tranquilizer = SD19_10_A,
  LP_Popper = SD19_11_A,
  LP_Anfetamines = SD19_12_A,
  LP_Heroine = SD19_13_A,
  # Last Month (LM) substance use
  LM_Alcohol = SD19_1_B,
  LM_Cigarette = SD19_2_B,
  LM_Cannabis = SD19_3_B,
```

```

LM_Cocaine = SD19_4_B,
LM_Basuco = SD19_5_B,
LM_Inhalant = SD19_6_B,
LM_Ecstasy = SD19_7_B,
LM_Psilocybin = SD19_8_B,
LM_LSD = SD19_9_B,
LM_TRAN = SD19_10_B,
LM_Popper = SD19_11_B,
LM_Anfetamines = SD19_12_B,
LM_Heroine = SD19_13_B,
# Last Week (LW) substance use
LW_Alcohol = SD19_1_C,
LW_Cigarette = SD19_2_C,
LW_Cannabis = SD19_3_C,
LW_Cocaine = SD19_4_C,
LW_Basuco = SD19_5_C,
LW_Inhalant = SD19_6_C,
LW_Ecstasy = SD19_7_C,
LW_Psilocybin = SD19_8_C,
LW_LSD = SD19_9_C,
LW_Tranquilizer = SD19_10_C,
LW_Popper = SD19_11_C,
LW_Anfetamines = SD19_12_C,
LW_Heroine = SD19_13_C,
Health = SD20_1,
# Health and other variables
Illness = SD21,
Disease_Other = SD22_13_TEXT,
PCPS1_4_Other = PCPS1_4_texto,
eed1_7_Other = EED1_7_TEXT
) |>
# Replace character "99" with NA for missing values
mutate(across(where(is.character), ~ na_if(., "99"))) |>
# Replace numeric 99 with NA for missing values
mutate(across(where(is.numeric), ~ na_if(., 99))) |>
# Recode gender categories into descriptive labels
mutate(
  Gender = recode(
    Gender,
    "1" = "Male",
    "2" = "Female",
    "3" = "Androgynous",
    "4" = "Trans woman",
    "5" = "Trans man",
    "6" = "Trans feminine",
    "7" = "Trans masculine",
    "8" = "Queer",
    "9" = "Non-binary",
    "10" = "Don't know",
    "11" = "Other"
  )
) |>
# Create a broader Gender category for analysis
mutate(Gender = if_else(Gender %in% c(
  "Woman", "Trans feminine", "Transexual", "Travesti", "Trans woman"
),

```

```

"Trans woman",
if_else(Gender %in% c("Man", "Trans masculine", "Trans man"),
  "Trans man",
  "Non-binary"
)
)) |>
# Recode housing categories into descriptive labels
mutate(
  Housing = recode(
    Housing,
    "1" = "Home-owner",
    "2" = "Renting (entire home)",
    "3" = "Living with family",
    "4" = "Shared rental (room)",
    "5" = "Without permanent housing"
  )
) |>
# Recode substance use responses from text to binary (1 = Yes, 0 = No)
mutate_at(
  c(
    "LP_Alcohol",
    "LP_Cigarette",
    "LP_Cannabis",
    "LP_Cocaine",
    "LP_Basuco",
    "LP_Inhalant",
    "LP_Ecstasy",
    "LP_Psilocybin",
    "LP_LSD",
    "LP_Tranquilizer",
    "LP_Popper",
    "LP_Anfetamines",
    "LP_Heroine",
    "LM_Alcohol",
    "LM_Cigarette",
    "LM_Cannabis",
    "LM_Cocaine",
    "LM_Basuco",
    "LM_Inhalant",
    "LM_Ecstasy",
    "LM_Psilocybin",
    "LM_LSD",
    "LM_TRAN",
    "LM_Popper",
    "LM_Anfetamines",
    "LM_Heroine",
    "LW_Alcohol",
    "LW_Cigarette",
    "LW_Cannabis",
    "LW_Cocaine",
    "LW_Basuco",
    "LW_Inhalant",
    "LW_Ecstasy",
    "LW_Psilocybin",
    "LW_LSD",
    "LW_Tranquilizer",
  )

```

```

    "LW_Popper",
    "LW_Anfetamines",
    "LW_Heroina"
  ),
  ~ recode(.x, "1" = 1, "2" = 0)
) |>
# Select only relevant variables
select(
  -c(
    Codigo,
    ends_with("_TEXT"),
    Sexualientation,
    ends_with("_texto")
  )
) |>
# Recode ethnicity, farmer status, marital status, SES, and education
mutate(
  Ethnicity = recode(
    Ethnicity,
    "1" = "Indigenous",
    "2" = "Rrom",
    "3" = "Afro-Colombian",
    "4" = "Afro-Colombian",
    "5" = "Afro-Colombian",
    "6" = "Afro-Colombian",
    "7" = "Afro-Colombian",
    "8" = "Afro-Colombian",
    "9" = "None"
  )
) |>
mutate(Farmer = recode(
  Farmer,
  "1" = "Yes",
  "2" = "No",
  "5" = NA_character_
)) |>
mutate(
  Marital_Status = recode(
    Marital_Status,
    "1" = "Married",
    "2" = "Single",
    "3" = "Widow/er",
    "4" = "Divorced",
    "5" = "Civil union",
    "6" = "Stable relationship"
  )
) |>
mutate(
  SES = recode_factor(
    SES,
    "1" = "Low",
    "2" = "Low",
    "7" = "Low",
    "3" = "Middle-low",
    "4" = "Middle-high",
    "5" = "High",

```

```

    "6" = "High"
  )
) |>
mutate(
  Education = recode_factor(
    Education,
    "1" = "No studies, illiterate",
    "2" = "No studies, literate",
    "3" = "Primary school (unfinished)",
    "4" = "Primary school",
    "5" = "Secondary school (unfinished)",
    "6" = "Secondary school",
    "7" = "Technical degree",
    "8" = "University (unfinished)",
    "9" = "University",
    "10" = "Postgraduate studies"
  )
) |>
mutate(across(
  c(
    SD22_1:SD22_13,
    EED1_1,
    EED1_2,
    EED1_3,
    EED1_4,
    EED1_5,
    EED1_6,
    EED1_7,
    EED2_1:EED2_5
  ),
  ~ as.numeric(
    recode(
      as.character(.x),
      "1" = "1",
      "2" = "0",
      .default = NA_character_,
      .missing = NA_character_
    )
  )
)) |>
# Convert disability variables to binary (1 = Has difficulty, 0 = No difficulty)
mutate(across(
  ends_with("_Difficulties"),
  ~ case_when(.x == 99 ~ NA_real_, is.na(.x) ~ NA_real_, .x == 4 ~ 1, TRUE ~ 0)
)) |>
# Create a new variable 'difficulty_dichotomous' to indicate whether a person has
# any difficulties across different categories
mutate(Difficulty_Dichotomous = if_else(
  # If any of the difficulties variables (e.g., Hearing_Difficulties, Speaking_Difficulties, etc.) are N
  rowSums(across(ends_with("_Difficulties"), ~ is.na(.))) > 0,
  NA_real_, # Assign NA if any difficulty is missing
  # Otherwise, check if all seven difficulties are marked as '1' (indicating impairment)
  if_else(rowSums(across(ends_with("_Difficulties"), ~ . == 1)) == 7,
    1, # Assign 1 if the person has all seven difficulties
    0 # Assign 0 otherwise
  )
)

```

```

)) |>
# Recode PCPS1_1 to PCPS1_5: Convert 1 to 1 (yes) and 2 to 0 (no), with NA for other values
mutate(across(PCPS1_1:PCPS1_5, ~ case_when(
  . == 1 ~ 1, # Yes
  . == 2 ~ 0, # No
  TRUE ~ NA_real_ # Missing or other values
))) |>
# Recode PCPS2_1 to PCPS2_5: Convert 1 to 0 (no engagement), and 2-5 to 1 (some engagement)
mutate(across(PCPS2_1:PCPS2_5, ~ case_when(
  . == 1 ~ 0, # No engagement
  . %in% 2:5 ~ 1, # Some engagement
  TRUE ~ NA_real_ # Missing or other values
))) |>
mutate(across(starts_with("EBD_"), ~ ifelse(is.na(.x), NA, .x - 1))) |>
# Compute aggregate variables summarizing different aspects
mutate(
  # Count the number of substances used in the last month
  Polyconsumption_Month = rowSums(across(LM_Alcohol:LM_Heroine, ~.), na.rm = TRUE),
  # Count the number of reported diseases or health conditions
  Disease_Burden = rowSums(across(SD22_1:SD22_13, ~.), na.rm = TRUE),
  # Count the number of group memberships (sum of binary indicators)
  Group_Membership = rowSums(across(PCPS1_1:PCPS1_5, ~.), na.rm = TRUE),
  # Count the number of community engagement activities
  Community_Engagement = rowSums(across(PCPS2_1:PCPS2_5, ~.), na.rm = TRUE),
  # The following line is commented out: it would sum discrimination experiences
  Discrimination = rowSums(across(EED1_1:EED1_7, ~.), na.rm = TRUE),
  Discrimination = ifelse(Discrimination >= 1, 1, 0),
  Self_Efficacy = if_else(rowSums(!is.na(across(starts_with("EAG_")))) >= 5,
    rowMeans(across(starts_with("EAG_")), na.rm = TRUE),
    NA_real_
  ),
  Life_Satisfaction = if_else(rowSums(!is.na(across(starts_with("SWLS_")))) >= 3,
    rowMeans(across(starts_with("SWLS_")), na.rm = TRUE),
    NA_real_
  ),
  Resilience = if_else(rowSums(!is.na(across(starts_with("EBR_")))) >= 3,
    rowMeans(across(starts_with("EBR_")), na.rm = TRUE),
    NA_real_
  ),
  Depression = if_else(rowSums(!is.na(across(starts_with("EBD_")))) >= 6,
    rowMeans(across(starts_with("EBD_")), na.rm = TRUE),
    NA_real_
  ),
  Social_Support = if_else(rowSums(!is.na(across(starts_with("MOS2_")))) >= 10,
    rowMeans(across(starts_with("MOS2_")), na.rm = TRUE),
    NA_real_
  ),
  Positive_Affect = if_else(rowSums(!is.na(across(all_of(PANAS_P)))) >= 8,
    rowMeans(across(all_of(PANAS_P)), na.rm = TRUE),
    NA_real_
  ),
  Negative_Affect = if_else(rowSums(!is.na(across(all_of(PANAS_N)))) >= 9,
    rowMeans(across(all_of(PANAS_N)), na.rm = TRUE),
    NA_real_
  ),
  Community_Cohesion = if_else(rowSums(!is.na(across(starts_with("PCPS3_")))) >= 2,

```



```

    rowMeans(across(starts_with("PCPS3_")), na.rm = TRUE),
    NA_real_
  ),
) |>
select(
  Age, Gender, Ethnicity, Marital_Status, SES, Education, Housing,
  Health, Polyconsumption_Month:Community_Cohesion
) |>
# Convert categorical variables Housing to Job into factors
mutate(Housing = as.factor(Housing)) |>
# Convert all remaining character variables to factors
mutate_if(is.character, as.factor) |>
filter(Age >= 18)

```

2.2 Missing Data

Create a summary of missing data for each variable in the final dataset

```

Missing_data <- data |>
# Summarize across all columns, counting the number of NA values in each column
summarise(across(everything(), ~ sum(is.na(.)))) |>
# Convert the summary from wide format (one row, many columns) to long format
pivot_longer(
  everything(), # Select all columns
  names_to = "Variable", # Store column names in a new variable "Variable"
  values_to = "NA_count" # Store the count of NAs in a new variable "NA_count"
) |>
# Compute the proportion of missing values for each variable
mutate(Proportion = NA_count / dim(data)[1]) # Divide NA count by total number of rows in 'data'

```

2.2.1 Fig. S1. Proportion of missing data

To apply multi-model inference techniques such as dredge and model averaging, models must be fitted with complete data. Therefore, assessing the proportion of missing data per variable was crucial. While excessive missingness could lead to unreliable models, imputing missing values might reduce data credibility. Since no variable had an unacceptably high proportion of missing data, we opted not to impute missing values.

```

Missing_data |>
mutate_at("Variable", str_replace_all, "_", " ") |>
ggplot(aes(
  x = fct_reorder(Variable, Proportion, .desc = TRUE), # Reorder variables from highest to lowest missingness
  y = Proportion,
  fill = Proportion # Use fill color to indicate proportion of missing data
)) +
geom_col() + # Create bar plot
# Add percentage labels on top of bars
geom_text(aes(label = percent(Proportion, accuracy = 1)),
  vjust = -0.5, size = 2
) +
# Apply color gradient: Green (low missing data) → Yellow (moderate) → Red (high missing data)
scale_fill_viridis_c(
  option = "plasma", # Define color range
  direction = -1, # Reverse the color scale
  labels = percent_format(accuracy = 1), # Convert legend values to percentage format
  alpha = 0.7
) +
# Convert Y-axis (proportion of missing data) to a percentage scale

```

```
scale_y_continuous(labels = scales::percent_format(accuracy = 1)) +
# Add axis labels
labs(
  y = "Percentage of Missing Data", # Label for Y-axis
  x = "Variable" # Label for X-axis
) +
# Use a minimal theme for a cleaner visual appearance
theme_minimal() +
# Rotate X-axis labels for better readability
theme(axis.text.x = element_text(angle = 60, hjust = 1))
```

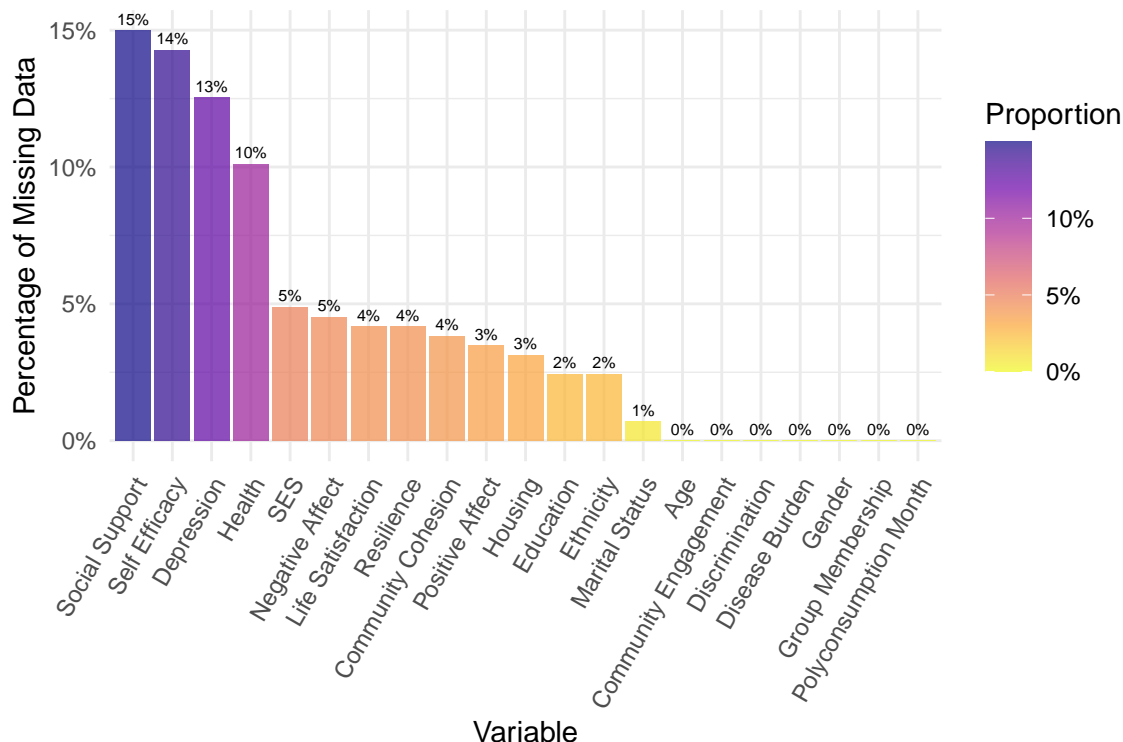


Figure S1. Proportion of missing data per variable. Variables are ordered from highest to lowest proportion of missing values. The color gradient indicates the proportion of missingness, with darker shades representing higher percentages.

3 Descriptives

3.1 Socio-demographic characteristics by gender

```
data |>
  select(Age:Housing) |>
  rename_with(~ gsub("_", " ", .x)) |>
  tbl_summary(by = Gender) |>
  add_n() |> # add column with total number of non-missing observations
  bold_labels() |>
  remove_footnote_header(columns = all_stat_cols()) |>
  as_kable_extra(
    format = "latex",
    linesep = "",
    booktabs = TRUE,
```

```
caption = "Sociodemographic characteristics of the study participants
          by gender identity"
) |>
kable_styling(latex_options = c("scale_down", "HOLD_position")) |>
footnote(
  general = "Values are presented as median (Q1, Q3) for Age and frequency (\\\\%)
            for the remaining variables.",
  threeparttable = TRUE,
  footnote_as_chunk = TRUE,
  escape = FALSE
)
```

Table S2. Sociodemographic characteristics of the study participants by gender identity

Characteristic	N	Non-binary N = 70	Trans man N = 28	Trans woman N = 189
Age	287	28 (24, 32)	27 (22, 35)	35 (28, 45)
Ethnicity	280			
Afro-Colombian		18 (26%)	10 (37%)	57 (31%)
Indigenous		5 (7.4%)	1 (3.7%)	17 (9.2%)
None		43 (63%)	15 (56%)	108 (58%)
Rrom		2 (2.9%)	1 (3.7%)	3 (1.6%)
Unknown		2	1	4
Marital Status	285			
Civil union		7 (10%)	6 (21%)	27 (14%)
Divorced		1 (1.4%)	0 (0%)	2 (1.1%)
Married		8 (11%)	4 (14%)	11 (5.9%)
Single		48 (69%)	13 (46%)	138 (74%)
Stable relationship		3 (4.3%)	4 (14%)	6 (3.2%)
Widow/er		3 (4.3%)	1 (3.6%)	3 (1.6%)
Unknown		0	0	2
SES	273			
Low		54 (81%)	20 (74%)	146 (82%)
Middle-low		12 (18%)	4 (15%)	29 (16%)
Middle-high		1 (1.5%)	2 (7.4%)	2 (1.1%)
High		0 (0%)	1 (3.7%)	2 (1.1%)
Unknown		3	1	10
Education	280			
No studies, illiterate		1 (1.5%)	1 (3.7%)	3 (1.6%)
No studies, literate		0 (0%)	0 (0%)	3 (1.6%)
Primary school (unfinished)		3 (4.4%)	0 (0%)	18 (9.7%)
Primary school		1 (1.5%)	0 (0%)	15 (8.1%)
Secondary school (unfinished)		12 (18%)	4 (15%)	54 (29%)
Secondary school		29 (43%)	9 (33%)	57 (31%)
Technical degree		13 (19%)	6 (22%)	23 (12%)
University (unfinished)		7 (10%)	5 (19%)	9 (4.9%)
University		1 (1.5%)	2 (7.4%)	3 (1.6%)
Postgraduate studies		1 (1.5%)	0 (0%)	0 (0%)
Unknown		2	1	4
Housing	278			
Home-owner		5 (7.4%)	2 (7.4%)	10 (5.5%)
Living with family		4 (5.9%)	3 (11%)	11 (6.0%)
Renting (entire home)		30 (44%)	17 (63%)	86 (47%)
Shared rental (room)		27 (40%)	4 (15%)	66 (36%)
Without permanent housing		2 (2.9%)	1 (3.7%)	10 (5.5%)
Unknown		2	1	6

Note: Values are presented as median (Q1, Q3) for Age and frequency (%) for the remaining variables.

3.2 Measured variables by gender

```
data |>
  select(Gender, Polyconsumption_Month:Community_Cohesion) |>
  rename_with(~ gsub("_", " ", .x)) |>
  tbl_summary(by = Gender) |>
  add_n() |> # add column with total number of non-missing observations
  bold_labels() |>
```

```
remove_footnote_header(columns = all_stat_cols()) |>
as_kable_extra(
  format = "latex",
  linesep = "",
  booktabs = TRUE,
  caption = "Other sociodemographic, health, and psychosocial characteristics
            of the study participants by gender identity"
) |>
kable_styling(latex_options = c("scale_down", "HOLD_position")) |>
footnote(
  general = "Continuous variables are presented as median (Q1, Q3), while categorical
            variables are shown as frequency (\\\\\\%).",
  threeparttable = TRUE,
  footnote_as_chunk = TRUE,
  escape = FALSE
)
```

Table S3. Other sociodemographic, health, and psychosocial characteristics of the study participants by gender identity

Characteristic	N	Non-binary N = 70	Trans man N = 28	Trans woman N = 189
Polyconsumption Month	287	2.00 (1.00, 3.00)	1.50 (0.50, 2.50)	2.00 (0.00, 3.00)
Disease Burden	287			
0		35 (50%)	11 (39%)	91 (48%)
1		20 (29%)	11 (39%)	58 (31%)
2		9 (13%)	3 (11%)	19 (10%)
3		2 (2.9%)	3 (11%)	8 (4.2%)
4		2 (2.9%)	0 (0%)	8 (4.2%)
5		1 (1.4%)	0 (0%)	3 (1.6%)
6		1 (1.4%)	0 (0%)	2 (1.1%)
Group Membership	287			
0		29 (41%)	10 (36%)	65 (34%)
1		32 (46%)	14 (50%)	84 (44%)
2		4 (5.7%)	2 (7.1%)	23 (12%)
3		1 (1.4%)	2 (7.1%)	9 (4.8%)
4		3 (4.3%)	0 (0%)	6 (3.2%)
5		1 (1.4%)	0 (0%)	2 (1.1%)
Community Engagement	287			
0		21 (30%)	4 (14%)	27 (14%)
1		9 (13%)	2 (7.1%)	43 (23%)
2		6 (8.6%)	6 (21%)	44 (23%)
3		11 (16%)	5 (18%)	39 (21%)
4		15 (21%)	8 (29%)	28 (15%)
5		8 (11%)	3 (11%)	8 (4.2%)
Discrimination	287	60 (86%)	21 (75%)	169 (89%)
Self Efficacy	246	3.20 (2.80, 3.68)	2.55 (2.25, 3.35)	3.44 (3.10, 3.80)
Unknown		10	8	23
Life Satisfaction	275	4.23 (3.20, 5.60)	4.60 (3.60, 5.20)	5.20 (3.50, 6.40)
Unknown		2	3	7
Resilience	275	4.00 (2.75, 4.75)	3.25 (2.00, 4.00)	4.25 (3.00, 5.00)
Unknown		5	1	6
Depression	251	1.38 (1.07, 1.86)	1.64 (1.29, 2.00)	1.50 (1.14, 1.86)
Unknown		6	6	24
Social Support	244	3.16 (2.34, 4.34)	3.00 (2.68, 3.74)	3.05 (2.32, 4.47)
Unknown		10	7	26
Positive Affect	277	3.65 (2.95, 4.40)	3.40 (3.00, 3.80)	4.10 (3.40, 4.70)
Unknown		2	1	7
Negative Affect	274	2.10 (1.60, 3.20)	2.45 (1.80, 3.20)	2.40 (1.80, 3.10)
Unknown		2	2	9
Community Cohesion	276	4.33 (2.67, 6.00)	3.83 (3.00, 5.33)	5.00 (4.00, 6.00)
Unknown		5	0	6

Note: Continuous variables are presented as median (Q1, Q3), while categorical variables are shown as frequency (%).

3.3 Correlations

```
# Compute correlations for all participants combined
dat.corr.ALL <- data |>
  select(Age, Polyconsumption_Month:Community_Cohesion) |> # Select numeric variables
  corr.stars() |>
  tail(-1) |>
```

```

rownames_to_column(var = " ")

# Compute correlations for non-binary participants
dat.corr.NB <- data |>
  filter(Gender == "Non-binary") |> # Select only non binary
  select(Age, Polyconsumption_Month:Community_Cohesion) |> # Select numeric variables
  corr.stars() |> # Compute correlation matrix with significance stars
  tail(-1) |>
  rownames_to_column(var = " ") # Move row names to a column

# Compute correlations for trans men
dat.corr.TM <- data |>
  filter(Gender == "Trans man") |> # Select only trans men
  select(Age, Polyconsumption_Month:Community_Cohesion) |> # Select numeric variables
  corr.stars() |>
  tail(-1) |>
  rownames_to_column(var = " ")

# Compute correlations for trans women
dat.corr.TW <- data |>
  filter(Gender == "Trans woman") |> # Select only trans women
  select(Age, Polyconsumption_Month:Community_Cohesion) |> # Select numeric variables
  corr.stars() |>
  tail(-1) |>
  rownames_to_column(var = " ")

# Format and combine the correlation tables
bind_rows(dat.corr.ALL, dat.corr.NB, dat.corr.TM, dat.corr.TW) |>
  rename_with(~ gsub("_", " ", .x)) |>
  mutate_at(" ", str_replace_all, "_", " ") |>
  kable(
    digits = 2, booktabs = TRUE,
    align = c("l", rep("c", 13)),
    linesep = "",
    caption = "Correlations between measured variables", escape = FALSE
  ) |>
  # Add grouped row labels for each participant group
  pack_rows("All participants",
    start_row = 1, end_row = 13, bold = FALSE,
    background = "lightgray"
  ) |>
  pack_rows("Non binary",
    start_row = 14, end_row = 26, bold = FALSE,
    background = "lightgray"
  ) |>
  pack_rows("Trans men",
    start_row = 27, end_row = 39, bold = FALSE,
    background = "lightgray"
  ) |>
  pack_rows("Trans women",
    start_row = 40, end_row = 52, bold = FALSE,
    background = "lightgray"
  ) |>
  # Apply LaTeX styling
  kable_styling(latex_options = c("HOLD_position", "scale_down")) |>
  column_spec(2:10, width = "2.2cm") |> # Adjust column widths

```

```
# Add footnote explaining correlation significance levels
footnote(
  general = paste0(
    "Values represent Spearman correlation coefficients ($\\\\\\\\rho$). ",
    "For significance, $^\\\\\\\\dagger p$ < 0.1, *$p$ < 0.05, ",
    "**$p$ < 0.01, ***$p$ < 0.001. ",
    "Significant correlations are in bold."
  ),
  threeparttable = TRUE, footnote_as_chunk = TRUE, escape = FALSE
) |>
landscape() # Rotate table for better readability in LaTeX
```


Table S4. Correlations between measured variables

	Age	Polyconsumption Month	Disease Burden	Group Membership	Community Engagement	Discrimination	Self Efficacy	Life Satisfaction	Resilience	Depression	Social Support	Positive Affect	Negative Affect
All participants													
Polyconsumption Month	-0.32***												
Disease Burden	0.16**	-0.03											
Group Membership	0.17**	-0.04	0.11 [†]										
Community Engagement	-0.01	0.01	0.07	0.42***									
Discrimination	-0.08	0.11 [†]	0.11 [†]	0.01	0.16**								
Self Efficacy	0.23***	-0.18**	-0.12 [†]	0.13*	0.06	0.04							
Life Satisfaction	0.11 [†]	-0.21***	-0.23***	0.22***	0.07	-0.16**	0.4***						
Resilience	0.17**	-0.14*	-0.07	0.29***	0.14*	-0.15*	0.49***	0.49***					
Depression	0.05	0.10	0.27***	0.13*	0.10	0.27***	-0.10	-0.21***	-0.05				
Social Support	0.14*	-0.06	-0.08	0.24***	0.12 [†]	-0.08	0.33***	0.33***	0.26***	-0.06			
Positive Affect	0.18**	-0.10	-0.10	0.26***	0.02	-0.02	0.45***	0.46***	0.42***	-0.02	0.33***		
Negative Affect	-0.11 [†]	0.19**	0.11 [†]	-0.06	-0.12*	0.17**	-0.09	-0.18**	-0.19**	0.38***	0.04	-0.02	
Community Cohesion	0.19**	-0.09	0.06	0.26***	0.25***	0.06	0.28***	0.25***	0.29***	0.23***	0.26***	0.3***	-0.03
Non binary													
Polyconsumption Month	-0.28*												
Disease Burden	0.22 [†]	0.01											
Group Membership	0.12	-0.02	0.06										
Community Engagement	-0.05	0.04	0.21 [†]	0.39***									
Discrimination	-0.03	0.05	0.23 [†]	0.18	0.24*								
Self Efficacy	0.35**	-0.3*	-0.05	0.03	0.21	0.03							
Life Satisfaction	0.33**	-0.34**	-0.10	0.05	0.00	-0.12	0.26*						
Resilience	0.19	-0.21 [†]	-0.04	0.17	0.19	-0.21 [†]	0.56***	0.48***					
Depression	0.31*	0.15	0.47***	0.32**	0.20	0.4**	0.11	0.01	0.13				
Social Support	0.14	0.13	0.08	0.12	0.05	-0.09	0.15	0.32*	0.05	0.15			
Positive Affect	0.27*	-0.06	-0.06	0.21 [†]	0.10	0.01	0.49***	0.27*	0.27*	0.20	0.22 [†]		
Negative Affect	0.01	0.21 [†]	0.10	-0.12	-0.02	0.47***	-0.17	-0.13	-0.26*	0.35**	0.02	0.18	
Community Cohesion	0.27*	0.02	0.17	0.31*	0.39**	0.09	0.3*	0.14	0.06	0.41**	0.23 [†]	0.20	0.09
Trans men													
Polyconsumption Month	-0.24												
Disease Burden	-0.04	-0.19											
Group Membership	-0.07	-0.07	0.47*										
Community Engagement	-0.15	0.18	0.22	0.55**									
Discrimination	-0.36 [†]	0.24	0.05	0.44*	0.51**								
Self Efficacy	0.07	-0.24	0.02	0.52*	0.05	0.25							
Life Satisfaction	0.19	0.21	-0.11	0.06	-0.19	0.04	0.21						
Resilience	-0.08	0.15	0.10	0.34 [†]	-0.16	-0.15	0.57*	0.12					
Depression	-0.16	0.05	0.35	0.49*	0.62**	0.49*	0.14	-0.21	-0.22				
Social Support	0.13	-0.37 [†]	-0.05	0.4 [†]	0.05	0.08	0.35	0.15	0.27	-0.14			
Positive Affect	0.27	-0.11	-0.10	0.31	-0.28	-0.18	0.34	0.30	0.61***	-0.29	0.44 [†]		
Negative Affect	-0.27	0.16	0.27	0.17	0.13	0.34 [†]	-0.01	-0.29	-0.34 [†]	0.58**	-0.15	-0.32	
Community Cohesion	-0.15	-0.01	0.14	0.4*	0.09	-0.04	0.5*	-0.06	0.34 [†]	0.22	0.27	0.25	0.16
Trans women													
Polyconsumption Month	-0.37***												
Disease Burden	0.21**	-0.03											
Group Membership	0.18*	-0.03	0.09										
Community Engagement	0.07	-0.02	-0.02	0.42***									
Discrimination	-0.08	0.11	0.08	-0.15*	0.06								
Self Efficacy	0.08	-0.14 [†]	-0.13 [†]	0.13 [†]	0.05	0.00							
Life Satisfaction	-0.03	-0.22**	-0.29***	0.28***	0.16*	-0.22**	0.46***						
Resilience	0.12	-0.16*	-0.09	0.31***	0.18*	-0.19*	0.42***	0.51***					
Depression	0.03	0.09	0.19*	0.02	-0.01	0.19*	-0.15 [†]	-0.3***	-0.07				
Social Support	0.14 [†]	-0.10	-0.14 [†]	0.27***	0.14 [†]	-0.11	0.43***	0.35***	0.32***	-0.11			
Positive Affect	0.06	-0.13 [†]	-0.12	0.24***	0.05	-0.07	0.41***	0.5***	0.41***	-0.05	0.37***		
Negative Affect	-0.18*	0.19*	0.11	-0.09	-0.2**	0.01	-0.06	-0.21**	-0.13 [†]	0.37***	0.07	-0.10	
Community Cohesion	0.16*	-0.13 [†]	0.01	0.2**	0.23**	0.01	0.21**	0.27***	0.33***	0.18*	0.27***	0.3***	-0.10

Note: Values represent Spearman correlation coefficients (ρ). For significance, [†] $p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. Significant correlations are in bold.

4 Multi-model Inference

This section outlines the multi-model inference approach used to examine predictors of various outcome variables. The strategy follows a systematic model selection process, accounting for model uncertainty.

For each outcome variable, we repeated the following steps:

1. Data Preparation

- Relevant predictors are selected from the cleaned dataset.
- Missing values are removed to ensure complete case analysis¹

2. Global Model Specification

- A linear model (`lm`) is specified, including a broad set of demographic, psychological, and social predictors.
- This full model represents all hypothesized influences on the outcome.

3. Model Selection via `dredge()`

- The `MuMIn::dredge()` function generates all possible **nested models** from the global model.
- Models are ranked by Akaike's Information Criterion corrected for small sample sizes (*AICc*).
- This helps identify the most parsimonious models while considering model uncertainty.

4. Model Averaging (`model.avg`)

- Models with $\Delta AICc < 2$ (within two *AICc* units of the top model) are averaged.
- This produces shrinkage estimates, ensuring robust coefficient estimates.

5. Results Interpretation

- Tables summarize the coefficient estimates, importance values, and significance levels.
- Figures visualize term estimates, confidence intervals, and predictor importance.

This process is repeated for each outcome variable in the following sections.

4.1 Life Satisfaction model

This section details the modelling process for Life Satisfaction, including data preparation, model selection using Akaike's Information Criterion corrected for small sample sizes (*AICc*), and model averaging based on the best-ranked models.

The global model includes a broad set of predictors representing demographic, psychological, and social factors, allowing us to explore their relative contributions to Life Satisfaction. The model selection procedure identifies the most parsimonious models while accounting for model uncertainty.

```
dat_LS <- data |>
  select(
    Life_Satisfaction, Age, Gender, Ethnicity, Marital_Status, Education, Housing,
    Self_Efficacy, Community_Cohesion, Depression, Social_Support, Polyconsumption_Month,
    Disease_Burden, Discrimination, Group_Membership, Community_Engagement
  ) |>
  drop_na()

global_LS <- lm(
  Life_Satisfaction ~ Age + Gender + Ethnicity + Marital_Status + Education +
    Housing + Self_Efficacy + Community_Cohesion + Depression +
    Social_Support + Polyconsumption_Month + Disease_Burden + Discrimination +
    Group_Membership + Community_Engagement,
```

¹To maximize the number of non-missing cases, we created separate datasets for each outcome variable. Since models generated by `dredge()` must not contain missing values (NA) to remain comparable, this approach ensures that each model includes the largest possible sample size.

```
data = dat_LS,
na.action = "na.fail"
)
```

4.1.1 Dredge

To identify the best-fitting models, we perform automated model selection using `MuMIn::dredge()`, which fits all possible models nested within the global model and ranks them based on *AICc*. This helps determine the most important predictors of Life Satisfaction while considering model uncertainty.

```
dr_LS <- dredge(
  global_LS,
  # trace = 2 # uncomment to see progress bar
)
```

4.1.1.1 Fig. S2. Dredge results of the Life Satisfaction model The plot below visualizes the model selection results, displaying the top 100 models ranked by *AICc*. Each row represents an individual model, with blue cells indicating included predictors. The height of each row reflects the model's Akaike weight ($w_i(AICc)$), representing its relative support in the model set.

```
LS_dredge_plot <- dredge.plot(dr_LS) # Run the function and store the result
```

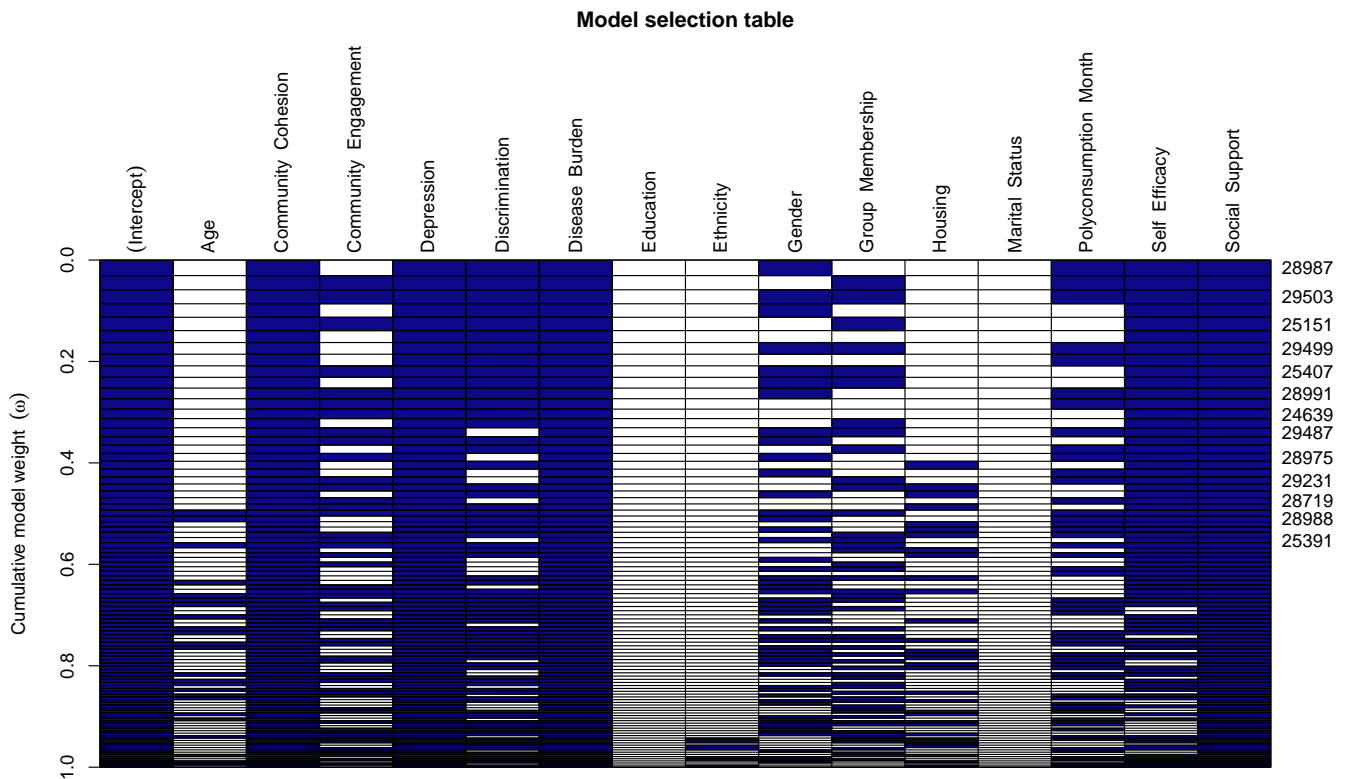


Figure S2. Model selection plot. Each row represents one of the top 100 models (ranked by *AICc*) out of 32,768 fitted models. Blue cells indicate included terms, with shading intensity reflecting their Akaike weight ($w_i(AICc)$). Row height corresponds to each model's relative support based on $w_i(AICc)$.

4.1.2 Average model

To account for model uncertainty, we compute an averaged model that combines estimates from all models with $\Delta AICc < 2$ (i.e., models within two $AICc$ units of the best-supported model). This approach produces more robust and conservative parameter estimates, reducing overconfidence in any single model.

```
avg_LS <- model.avg(dr_LS, subset = delta < 2, fit = TRUE)
```

4.1.2.1 Table S5. Term estimates for the Life Satisfaction model The table below presents coefficient estimates from the full average model, including 95% confidence intervals, standard errors, and significance levels.

```
tab_avg_LS <- avg.mod.summary(avg_LS, data = dat_LS)
tab_avg_LS$table
```

Table S5. Coefficient estimates for the Life Satisfaction model.

Term	<i>B</i>	95% <i>CI</i> s	<i>z</i>	<i>p</i>
(Intercept)	2.935	1.394 — 4.476	3.733	< 0.001
Age	0.000	-0.004 — 0.003	0.090	0.93
Community Cohesion	0.237	0.086 — 0.389	3.073	0.0021
Community Engagement	-0.061	-0.212 — 0.091	0.784	0.43
Depression	-0.572	-0.943 — -0.202	3.028	0.0025
Discrimination	-0.541	-1.276 — 0.195	1.441	0.15
Disease Burden	-0.234	-0.397 — -0.071	2.815	0.0049
Gender: Trans man	0.281	-0.504 — 1.067	0.702	0.48
Gender: Trans woman	0.247	-0.327 — 0.82	0.843	0.4
Group Membership	0.075	-0.136 — 0.285	0.696	0.49
Housing: Living with family	-0.144	-1.033 — 0.746	0.316	0.75
Housing: Renting (entire home)	-0.043	-0.419 — 0.332	0.227	0.82
Housing: Shared rental (room)	-0.066	-0.538 — 0.405	0.275	0.78
Housing: Without permanent housing	-0.107	-0.827 — 0.613	0.291	0.77
Polyconsumption Month	-0.031	-0.105 — 0.044	0.800	0.42
Self Efficacy	0.413	0.043 — 0.784	2.189	0.0286
Social Support	0.313	0.121 — 0.505	3.190	0.0014

Note: This table includes estimates based on a full model average. The full model average ensures that all variables are included in every model, with coefficients set to zero when absent. As a consequence, it acts as a shrinkage estimator, making estimates more conservative. *B* represents unstandardized model coefficients. Reference levels: Gender = Non-binary; Housing = Home-owner. Significant effects are in bold.

4.1.2.2 Fig. S3. Term estimates for the Life Satisfaction model This figure represents parameter estimates from the model-averaged coefficients.

```
fig_avg_LS <- avg.mod.plot(avg_LS)
fig_avg_LS
```

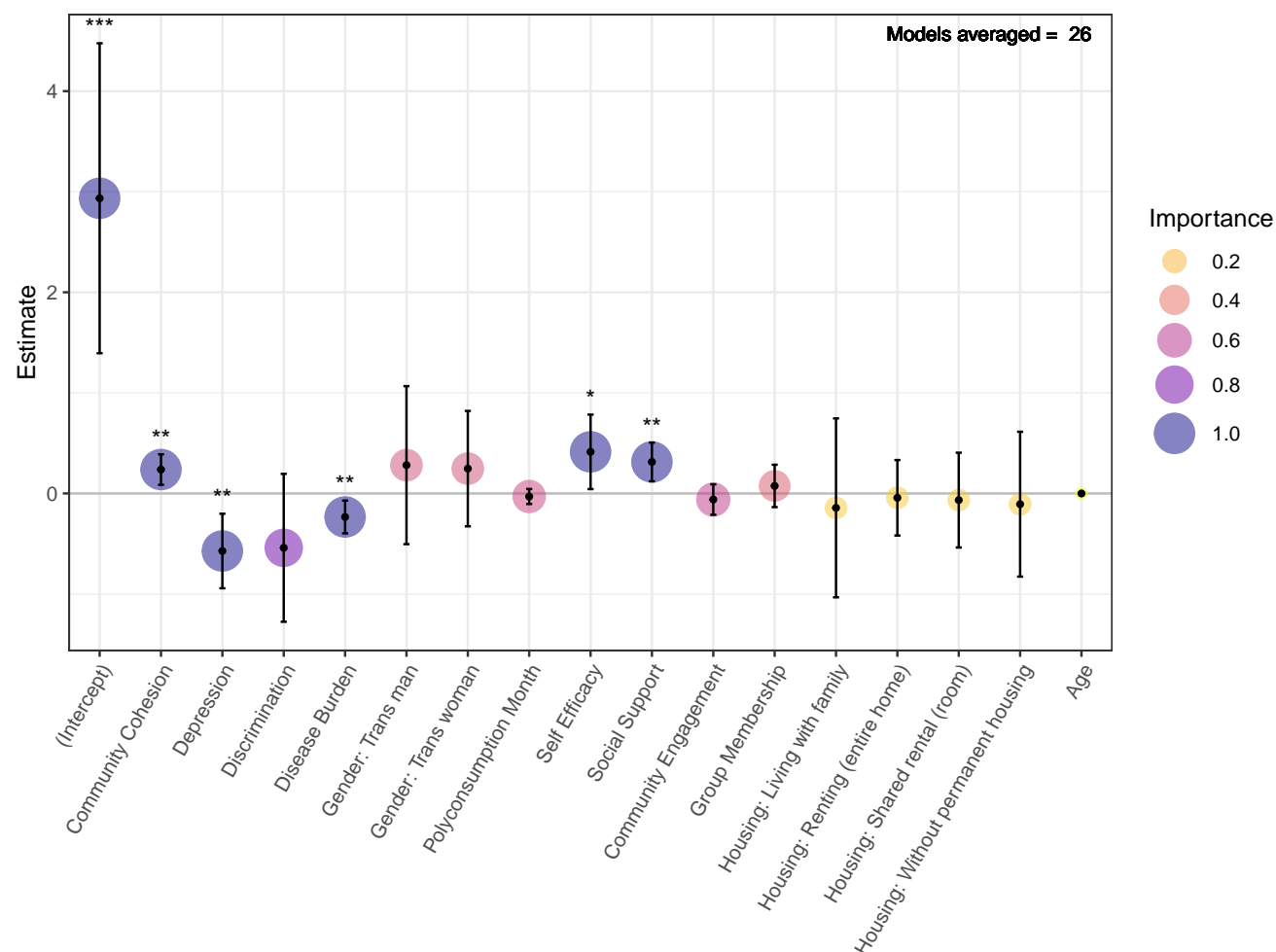


Figure S3. Term estimates with 95% confidence intervals for the final model average of the best (AICc $\Delta < 2$) models predicting Life Satisfaction. Importance is the proportion of averaged models in which a term appears (i.e. an Importance of 0.5 means that the term is included in half the averaged models, and an Importance of 1.0 means that all the averaged models included that term). Larger and darker points indicate higher importance. Confidence intervals show uncertainty in effect size estimates. For term significance: † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

4.2 PANAS Positive Affect model

This section details the modelling process for PANAS Positive Affect, including data preparation, model selection using Akaike’s Information Criterion corrected for small sample sizes (*AICc*), and model averaging based on the best-ranked models.

The global model includes a broad set of predictors representing demographic, psychological, and social factors, allowing us to explore their relative contributions to PANAS Positive Affect. The model selection procedure identifies the most parsimonious models while accounting for model uncertainty.

```
dat_PANAS_P <- data |>
  select(
    Positive_Affect, Age, Gender, Ethnicity, Marital_Status, Education, Housing,
    Self_Efficacy, Community_Cohesion, Depression, Social_Support, Polyconsumption_Month,
    Disease_Burden, Discrimination, Group_Membership, Community_Engagement
  ) |>
  drop_na()
```

```
global_PANAS_P <- lm(
  Positive_Affect ~ Age + Gender + Ethnicity + Marital_Status + Education +
    Housing + Self_Efficacy + Community_Cohesion + Depression +
    Social_Support + Polyconsumption_Month + Disease_Burden + Discrimination +
    Group_Membership + Community_Engagement,
  data = dat_PANAS_P,
  na.action = "na.fail"
)
```

4.2.1 Dredge

To identify the best-fitting models, we perform automated model selection using `MuMIn::dredge()`, which fits all possible models nested within the global model and ranks them based on *AICc*. This helps determine the most important predictors of PANAS Positive Affect while considering model uncertainty.

```
dr_PANAS_P <- dredge(
  global_PANAS_P,
  # trace = 2 # uncomment to see progress bar
)
```

4.2.1.1 Fig. S4. Dredge results of the PANAS Positive Affect model The plot below visualizes the model selection results, displaying the top 100 models ranked by *AICc*. Each row represents an individual model, with blue cells indicating included predictors. The height of each row reflects the model's Akaike weight ($w_i(AICc)$), representing its relative support in the model set.

```
PANAS_P_dredge_plot <- dredge.plot(dr_PANAS_P) # Run the function and store the result
```

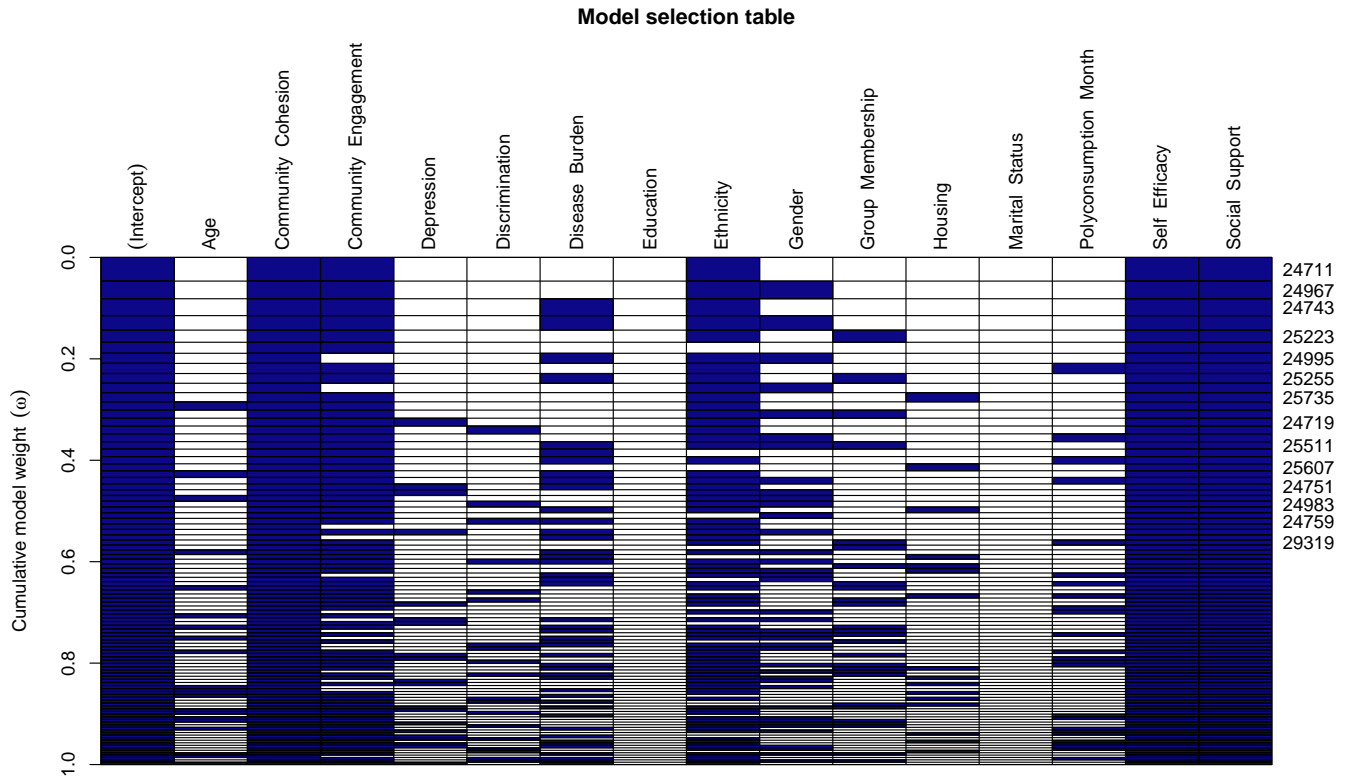


Figure S4. Model selection plot. Each row represents one of the top 100 models (ranked by $AICc$) out of 32,768 fitted models. Blue cells indicate included terms, with shading intensity reflecting their Akaike weight ($w_i(AICc)$). Row height corresponds to each model's relative support based on $w_i(AICc)$.

4.2.2 Average model

To account for model uncertainty, we compute an averaged model that combines estimates from all models with $\Delta AICc < 2$ (i.e., models within two $AICc$ units of the best-supported model). This approach produces more robust and conservative parameter estimates, reducing overconfidence in any single model.

```
avg_PANAS_P <- model.avg(dr_PANAS_P, subset = delta < 2, fit = TRUE)
```

4.2.2.1 Table S6. Term estimates for the PANAS Positive Affect model The table below presents coefficient estimates from the full average model, including 95% confidence intervals, standard errors, and significance levels.

```
tab_avg_PANAS_P <- avg.mod.summary(avg_PANAS_P, data = dat_PANAS_P)
tab_avg_PANAS_P$table
```

Table S6. Coefficient estimates for the Positive Affect model.

Term	<i>B</i>	95% <i>CI</i> s	<i>z</i>	<i>p</i>
(Intercept)	0.649	-0.118 — 1.416	1.658	0.1
Community Cohesion	0.127	0.044 — 0.21	2.998	0.0027
Community Engagement	-0.073	-0.167 — 0.02	1.535	0.12
Disease Burden	-0.021	-0.099 — 0.056	0.538	0.59
Ethnicity: Indigenous	0.311	-0.134 — 0.756	1.369	0.17
Ethnicity: None	0.248	-0.051 — 0.547	1.625	0.1
Ethnicity: Rrom	0.817	0.014 — 1.62	1.995	0.046
Gender: Trans man	0.028	-0.252 — 0.309	0.198	0.84
Gender: Trans woman	0.098	-0.204 — 0.399	0.634	0.53
Group Membership	0.009	-0.053 — 0.07	0.281	0.78
Housing: Living with family	0.004	-0.156 — 0.164	0.051	0.96
Housing: Renting (entire home)	0.027	-0.208 — 0.262	0.224	0.82
Housing: Shared rental (room)	0.011	-0.136 — 0.158	0.144	0.89
Housing: Without permanent housing	0.024	-0.225 — 0.272	0.188	0.85
Polyconsumption Month	-0.001	-0.013 — 0.011	0.153	0.88
Self Efficacy	0.584	0.379 — 0.789	5.589	< 0.0001
Social Support	0.185	0.077 — 0.294	3.356	< 0.001

Note: This table includes estimates based on a full model average. The full model average ensures that all variables are included in every model, with coefficients set to zero when absent. As a consequence, it acts as a shrinkage estimator, making estimates more conservative. *B* represents unstandardized model coefficients. Reference levels: Gender = Non-binary; Ethnicity = Afro-Colombian; Housing = Home-owner. Significant effects are in bold.

4.2.2.2 Fig. S5. Term estimates for the PANAS Positive Affect model This figure represents parameter estimates from the model-averaged coefficients.

```
fig_avg_PANAS_P <- avg.mod.plot(avg_PANAS_P)
fig_avg_PANAS_P
```

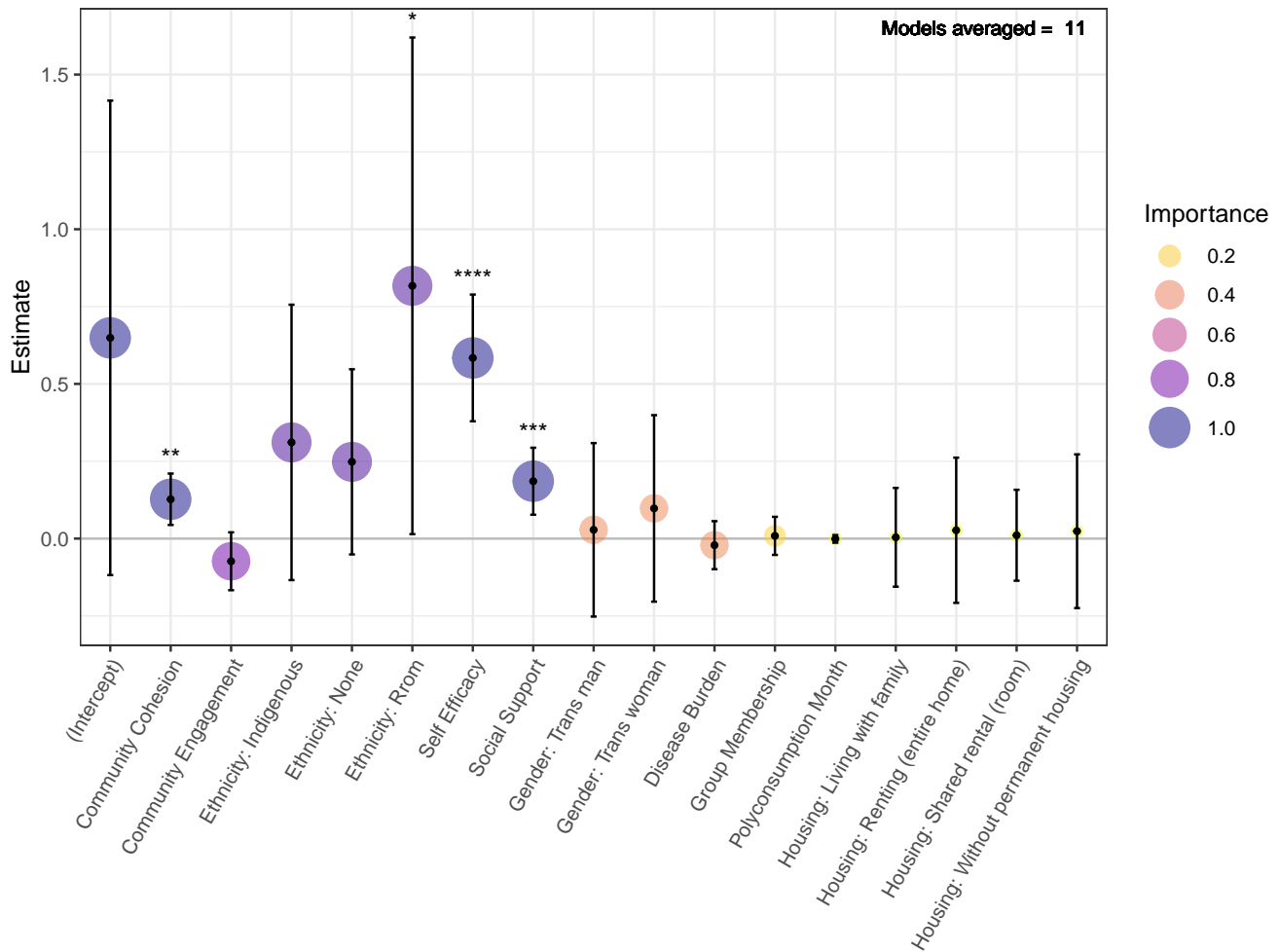



Figure S5. Term estimates with 95% confidence intervals for the final model average of the best ($AICc \Delta < 2$) models predicting PANAS Positive Affect. Importance is the proportion of averaged models in which a term appears (i.e. an Importance of 0.5 means that the term is included in half the averaged models, and an Importance of 1.0 means that all the averaged models included that term). Larger and darker points indicate higher importance. Confidence intervals show uncertainty in effect size estimates. For term significance: † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

4.3 PANAS Negative Affect model

This section details the modelling process for PANAS Negative Affect, including data preparation, model selection using Akaike's Information Criterion corrected for small sample sizes ($AICc$), and model averaging based on the best-ranked models.

The global model includes a broad set of predictors representing demographic, psychological, and social factors, allowing us to explore their relative contributions to PANAS Negative Affect. The model selection procedure identifies the most parsimonious models while accounting for model uncertainty.

```
dat_PANAS_N <- data |>
  select(
    Negative_Affect, Age, Gender, Ethnicity, Marital_Status, Education, Housing,
    Self_Efficacy, Community_Cohesion, Depression, Social_Support, Polyconsumption_Month,
    Disease_Burden, Discrimination, Group_Membership, Community_Engagement
  ) |>
  drop_na()
```

```
global_PANAS_N <- lm(
  Negative_Affect ~ Age + Gender + Ethnicity + Marital_Status + Education +
    Housing + Self_Efficacy + Community_Cohesion + Depression +
    Social_Support + Polyconsumption_Month + Disease_Burden + Discrimination +
    Group_Membership + Community_Engagement,
  data = dat_PANAS_N,
  na.action = "na.fail"
)
```

4.3.1 Dredge

To identify the best-fitting models, we perform automated model selection using `MuMIn::dredge()`, which fits all possible models nested within the global model and ranks them based on *AICc*. This helps determine the most important predictors of PANAS Negative Affect while considering model uncertainty.

```
dr_PANAS_N <- dredge(
  global_PANAS_N,
  # trace = 2 # uncomment to see progress bar
)
```

4.3.1.1 Fig. S6. Dredge results of the PANAS Negative Affect model The plot below visualizes the model selection results, displaying the top 100 models ranked by *AICc*. Each row represents an individual model, with blue cells indicating included predictors. The height of each row reflects the model's Akaike weight ($w_i(AICc)$), representing its relative support in the model set.

```
PANAS_N_dredge_plot <- dredge.plot(dr_PANAS_N) # Run the function and store the result
```

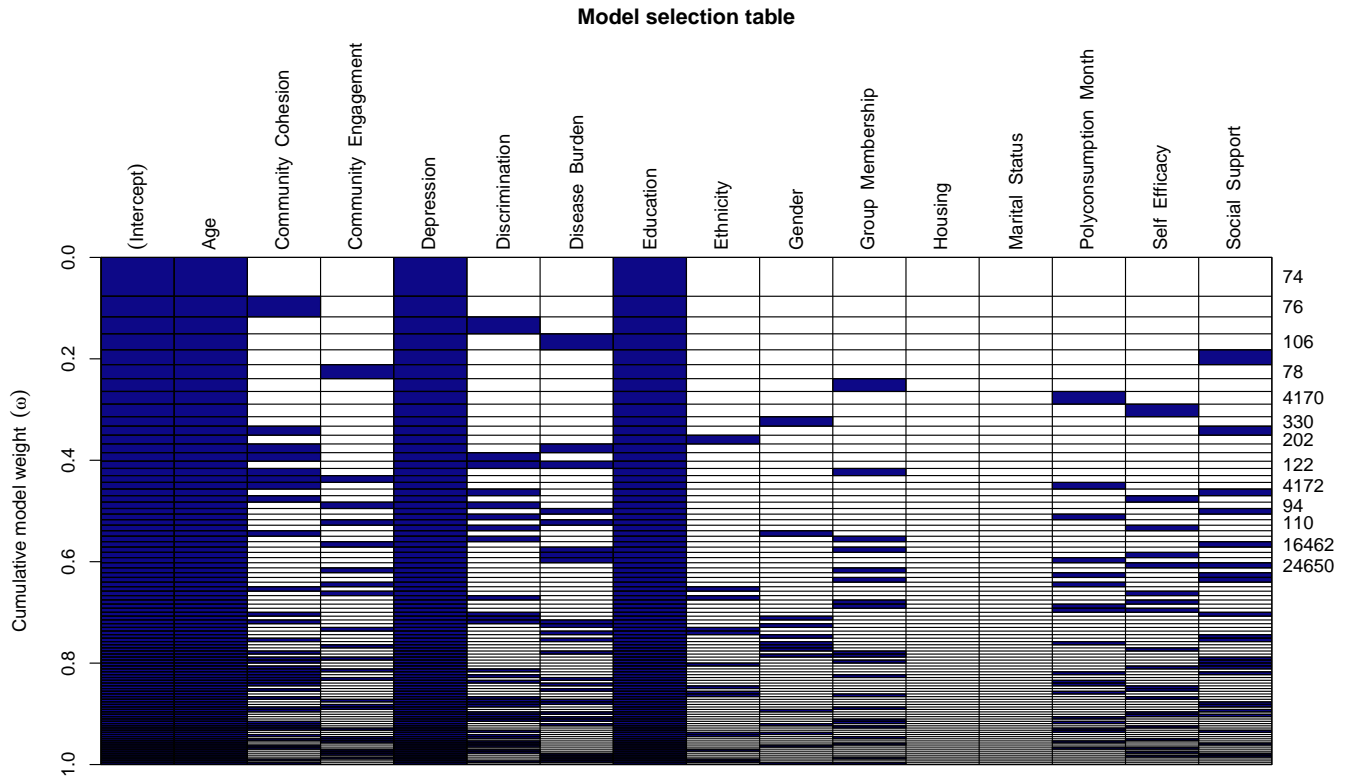


Figure S6. Model selection plot. Each row represents one of the top 100 models (ranked by $AICc$) out of 32,768 fitted models. Blue cells indicate included terms, with shading intensity reflecting their Akaike weight ($w_i(AICc)$). Row height corresponds to each model's relative support based on $w_i(AICc)$.

4.3.2 Average model

To account for model uncertainty, we compute an averaged model that combines estimates from all models with $\Delta AICc < 2$ (i.e., models within two $AICc$ units of the best-supported model). This approach produces more robust and conservative parameter estimates, reducing overconfidence in any single model.

```
avg_PANAS_N <- model.avg(dr_PANAS_N, subset = delta < 2, fit = TRUE)
```

4.3.2.1 Table S7. Term estimates for the PANAS Negative Affect model The table below presents coefficient estimates from the full average model, including 95% confidence intervals, standard errors, and significance levels.

```
tab_avg_PANAS_N <- avg.mod.summary(avg_PANAS_N, data = dat_PANAS_N)
tab_avg_PANAS_N$table
```

Table S7. Coefficient estimates for the Negative Affect model.

Term	<i>B</i>	95% <i>CI</i> s	<i>z</i>	<i>p</i>
(Intercept)	2.768	1.605 — 3.932	4.663	< 0.0001
Age	-0.019	-0.03 — -0.008	3.426	< 0.001
Community Cohesion	-0.009	-0.063 — 0.045	0.321	0.75
Depression	0.692	0.481 — 0.904	6.415	< 0.0001
Discrimination	0.024	-0.163 — 0.211	0.249	0.8
Disease Burden	-0.005	-0.053 — 0.042	0.225	0.82
Education: No studies, literate	0.247	-1.306 — 1.8	0.312	0.76
Education: Primary school	-0.591	-1.679 — 0.496	1.066	0.29
Education: Primary school (unfinished)	-0.177	-1.239 — 0.885	0.326	0.74
Education: Secondary school	-0.638	-1.649 — 0.372	1.238	0.22
Education: Secondary school (unfinished)	-0.679	-1.696 — 0.337	1.310	0.19
Education: Technical degree	-1.327	-2.378 — -0.275	2.472	0.0134
Education: University	-1.619	-2.87 — -0.368	2.537	0.0112
Education: University (unfinished)	-1.081	-2.169 — 0.007	1.948	0.05
Social Support	0.004	-0.041 — 0.05	0.190	0.85

Note: This table includes estimates based on a full model average. The full model average ensures that all variables are included in every model, with coefficients set to zero when absent. As a consequence, it acts as a shrinkage estimator, making estimates more conservative. *B* represents unstandardized model coefficients. Reference levels: Education = No studies, illiterate. Significant effects are in bold.

4.3.2.2 Fig. S7. Term estimates for the PANAS Negative Affect model This figure represents parameter estimates from the model-averaged coefficients.

```
fig_avg_PANAS_N <- avg.mod.plot(avg_PANAS_N)
fig_avg_PANAS_N
```

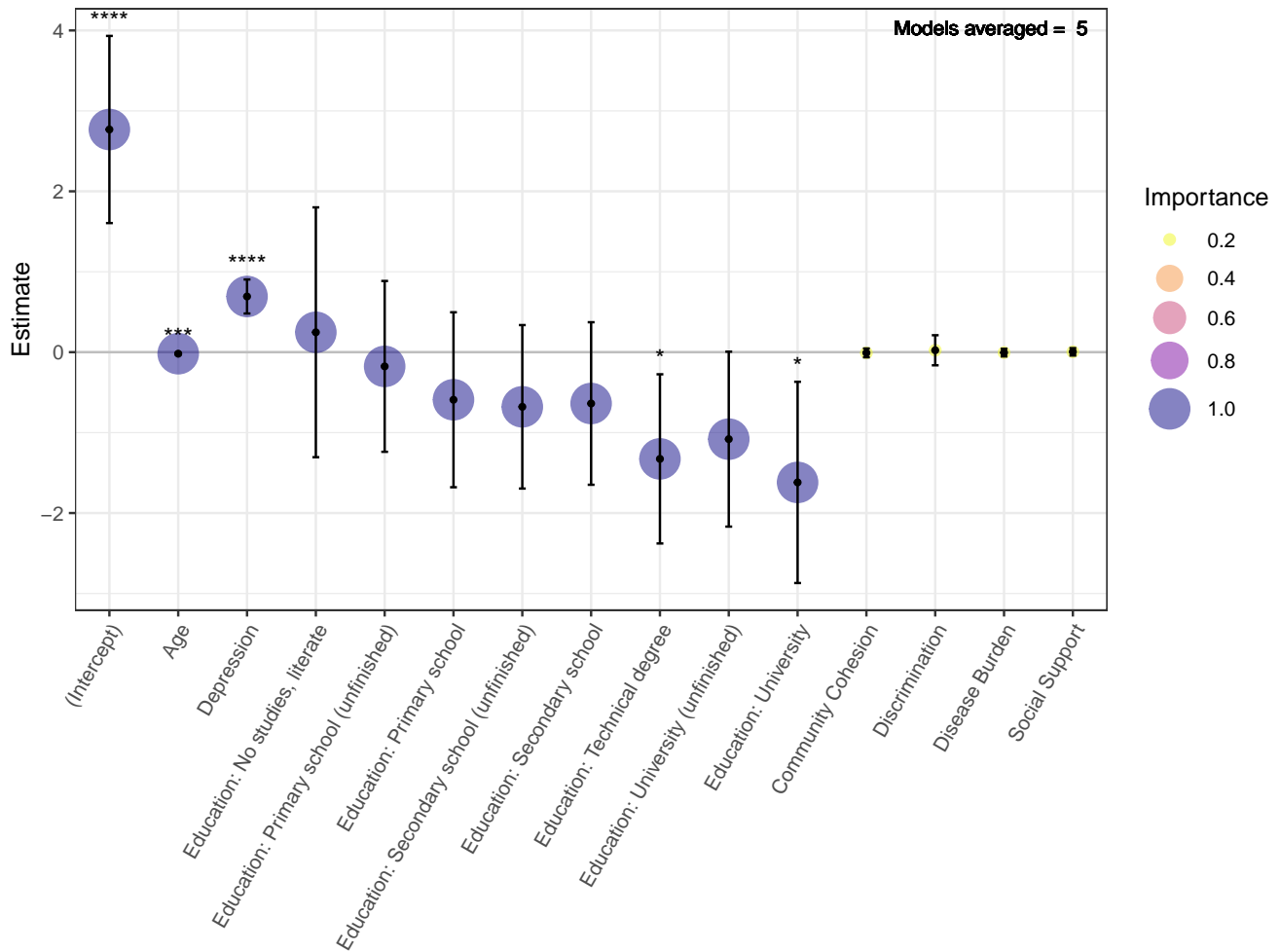


Figure S7. Term estimates with 95% confidence intervals for the final model average of the best (AICc $\Delta < 2$) models predicting PANAS Negative Affect. Importance is the proportion of averaged models in which a term appears (i.e. an Importance of 0.5 means that the term is included in half the averaged models, and an Importance of 1.0 means that all the averaged models included that term). Larger and darker points indicate higher importance. Confidence intervals show uncertainty in effect size estimates. For term significance: † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

5 Final figures and tables

5.1 Tab. 1. Term estimates for the three final averaged model

```
tab_avg_LS$coefficients |>
  full_join(tab_avg_PANAS_P$coefficients, by = "term") |>
  full_join(tab_avg_PANAS_N$coefficients, by = "term") |>
  arrange(term) |>
  kable(digits = 3,
        booktabs = TRUE,
        linesep = "",
        align = c("l", rep("c", 12)),
        caption = "Coefficient estimates for the the three final averaged models",
        col.names = c("Term",
                      rep(c("$B$", "$95 \\% CIs$", "$z$", "$p$"), times = 3)),
```

```

escape = FALSE
) |>
kable_styling(latex_options = c("scale_down", "HOLD_position")) |>
add_header_above(c(" ",
                    "Life Satisfaction" = 4,
                    "PANAS Positive Affect" = 4,
                    "PANAS Negative Affect" = 4)) |>
column_spec(c(5, 9), border_right = TRUE) |>
footnote(
  general = paste0(
    "This table includes estimates based on full model averages. ",
    "The full model average ensures that all predictors present in any
    averaged model are included, with coefficients set to zero when absent.
    As a consequence, it acts as a shrinkage ",
    "estimator, making estimates more conservative. ",
    "$B$ represents unstandardized model coefficients for each of the three models:
    Life Satisfaction(", tab_avg_LS$reference_levels, "),
    PANAS Positive Affect(", tab_avg_PANAS_P$reference_levels, "),
    and PANAS Negative Affect(", tab_avg_PANAS_N$reference_levels, ").",
    " Significant effects are in bold."
  ),
  threeparttable = TRUE,
  footnote_as_chunk = TRUE,
  escape = FALSE
)

```

Table 1. Coefficient estimates for the the three final averaged models

Term	Life Satisfaction				PANAS Positive Affect				PANAS Negative Affect			
	<i>B</i>	95% <i>CI</i> s	<i>z</i>	<i>p</i>	<i>B</i>	95% <i>CI</i> s	<i>z</i>	<i>p</i>	<i>B</i>	95% <i>CI</i> s	<i>z</i>	<i>p</i>
(Intercept)	2.935	1.394 — 4.476	3.733	< 0.001	0.649	-0.118 — 1.416	1.658	0.1	2.768	1.605 — 3.932	4.663	< 0.0001
Age	0.000	-0.004 — 0.003	0.090	0.93					-0.019	-0.03 — -0.008	3.426	< 0.001
Community Cohesion	0.237	0.086 — 0.389	3.073	0.0021	0.127	0.044 — 0.21	2.998	0.0027	-0.009	-0.063 — 0.045	0.321	0.75
Community Engagement	-0.061	-0.212 — 0.091	0.784	0.43	-0.073	-0.167 — 0.02	1.535	0.12				
Depression	-0.572	-0.943 — -0.202	3.028	0.0025					0.692	0.481 — 0.904	6.415	< 0.0001
Discrimination	-0.541	-1.276 — -0.195	1.441	0.15					0.024	-0.163 — 0.211	0.249	0.8
Disease Burden	-0.234	-0.397 — -0.071	2.815	0.0049	-0.021	-0.099 — 0.056	0.538	0.59	-0.005	-0.053 — 0.042	0.225	0.82
Education: No studies, literate									0.247	-1.306 — 1.8	0.312	0.76
Education: Primary school									-0.591	-1.679 — 0.496	1.066	0.29
Education: Primary school (unfinished)									-0.177	-1.239 — 0.885	0.326	0.74
Education: Secondary school									-0.638	-1.649 — 0.372	1.238	0.22
Education: Secondary school (unfinished)									-0.679	-1.696 — 0.337	1.310	0.19
Education: Technical degree									-1.327	-2.378 — -0.275	2.472	0.0134
Education: University									-1.619	-2.87 — -0.368	2.537	0.0112
Education: University (unfinished)									-1.081	-2.169 — 0.007	1.948	0.05
Ethnicity: Indigenous					0.311	-0.134 — 0.756	1.369	0.17				
Ethnicity: None					0.248	-0.051 — 0.547	1.625	0.1				
Ethnicity: Rrom					0.817	0.014 — 1.62	1.995	0.046				
Gender: Trans man	0.281	-0.504 — 1.067	0.702	0.48	0.028	-0.252 — 0.309	0.198	0.84				
Gender: Trans woman	0.247	-0.327 — 0.82	0.843	0.4	0.098	-0.204 — 0.399	0.634	0.53				
Group Membership	0.075	-0.136 — 0.285	0.696	0.49	0.009	-0.053 — 0.07	0.281	0.78				
Housing: Living with family	-0.144	-1.033 — 0.746	0.316	0.75	0.004	-0.156 — 0.164	0.051	0.96				
Housing: Renting (entire home)	-0.043	-0.419 — 0.332	0.227	0.82	0.027	-0.208 — 0.262	0.224	0.82				
Housing: Shared rental (room)	-0.066	-0.538 — 0.405	0.275	0.78	0.011	-0.136 — 0.158	0.144	0.89				
Housing: Without permanent housing	-0.107	-0.827 — 0.613	0.291	0.77	0.024	-0.225 — 0.272	0.188	0.85				
Polyconsumption Month	-0.031	-0.105 — 0.044	0.800	0.42	-0.001	-0.013 — 0.011	0.153	0.88				
Self Efficacy	0.413	0.043 — 0.784	2.189	0.0286	0.584	0.379 — 0.789	5.589	< 0.0001				
Social Support	0.313	0.121 — 0.505	3.190	0.0014	0.185	0.077 — 0.294	3.356	< 0.001	0.004	-0.041 — 0.05	0.190	0.85

Note: This table includes estimates based on full model averages. The full model average ensures that all predictors present in any averaged model are included, with coefficients set to zero when absent. As a consequence, it acts as a shrinkage estimator, making estimates more conservative. *B* represents unstandardized model coefficients for each of the three models: Life Satisfaction(Reference levels: Gender = Non-binary; Housing = Home-owner), PANAS Positive Affect(Reference levels: Gender = Non-binary; Ethnicity = Afro-Colombian; Housing = Home-owner), and PANAS Negative Affect(Reference levels: Education = No studies, illiterate). Significant effects are in bold.

5.2 Fig. 1. Term estimates for the three final averaged model

This figure represents parameter estimates from the model-averaged coefficients.

```

ggarrange(
  fig_avg_LS +

```

```
  labs(subtitle = "Life Satisfaction") +
  theme(legend.position = "none"),
fig_avg_PANAS_P +
  labs(subtitle = "PANAS Possitive Affect") +
  theme(legend.position = "none"),
fig_avg_PANAS_N +
  labs(subtitle = "PANAS Negative Affect") +
  theme(legend.position = "none"),
as_ggplot(get_legend(fig_avg_LS)),
ncol = 2,
nrow = 2,
labels = c("a", "b", "c", NULL)
)
```

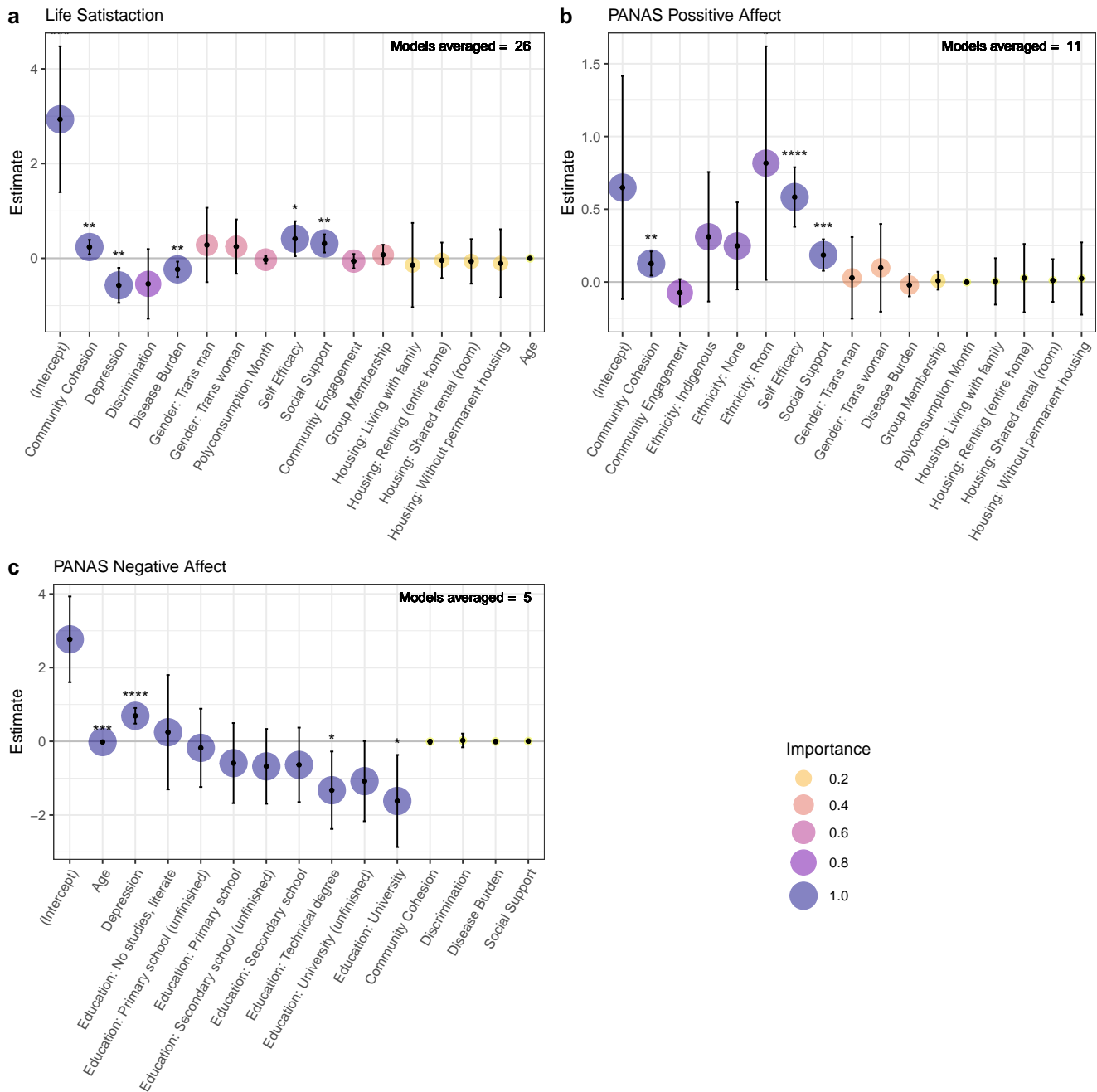


Figure 1. Term estimates with 95% confidence intervals for the final model averages of the best ($AIC_c \Delta < 2$) models predicting (a) Life Satisfaction, (b) PANAS Positive Affect, and (c) PANAS Negative Affect. Importance is the proportion of averaged models in which a term appears (i.e. an Importance of 0.5 means that the term is included in half the averaged models, and an Importance of 1.0 means that all the averaged models included that term). Larger and darker points indicate higher importance. Confidence intervals show uncertainty in effect size estimates. For term significance: † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; **** $p < 0.0001$.

6 Session info (for reproducibility)

```
# Display session information for reproducibility
# - Uses `pander()` for better formatting
```



```
# - `locale = FALSE` to exclude locale-specific info (reduces clutter)
library(pander)
pander(sessionInfo(), locale = FALSE)
```

R version 4.4.3 (2025-02-28)

Platform: x86_64-pc-linux-gnu

attached base packages: *stats*, *graphics*, *grDevices*, *utils*, *datasets*, *methods* and *base*

other attached packages: *pander*(v.0.6.6), *Hmisc*(v.5.2-3), *gtsummary*(v.2.1.0), *ggpubr*(v.0.6.0), *lubridate*(v.1.9.4), *forcats*(v.1.0.0), *stringr*(v.1.5.1), *dplyr*(v.1.1.4), *purrr*(v.1.0.4), *tidyr*(v.1.3.1), *tibble*(v.3.2.1), *ggplot2*(v.3.5.1), *tidyverse*(v.2.0.0), *car*(v.3.1-3), *carData*(v.3.0-5), *kableExtra*(v.1.4.0), *scales*(v.1.3.0), *readr*(v.2.1.5), *performance*(v.0.13.0), *MuMIn*(v.1.48.4), *psych*(v.2.4.12), *lrm*(v.1.2-0), *polycor*(v.0.8-1), *msm*(v.1.8.2), *MASS*(v.7.3-65) and *knitr*(v.1.50)

loaded via a namespace (and not attached): *tidyselect*(v.1.2.1), *viridisLite*(v.0.4.2), *farver*(v.2.1.2), *fastmap*(v.1.2.0), *digest*(v.0.6.37), *rpart*(v.4.1.24), *timechange*(v.0.3.0), *lifecycle*(v.1.0.4), *cluster*(v.2.1.8.1), *survival*(v.3.8-3), *magrittr*(v.2.0.3), *compiler*(v.4.4.3), *rlang*(v.1.1.5), *tools*(v.4.4.3), *yaml*(v.2.3.10), *data.table*(v.1.17.0), *ggsignif*(v.0.6.4), *labeling*(v.0.4.3), *htmlwidgets*(v.1.6.4), *bit*(v.4.6.0), *mnormt*(v.2.1.1), *xmll2*(v.1.3.8), *abind*(v.1.4-8), *expm*(v.1.0-0), *withr*(v.3.0.2), *foreign*(v.0.8-88), *nnet*(v.7.3-20), *grid*(v.4.4.3), *stats4*(v.4.4.3), *colorspace*(v.2.1-1), *insight*(v.1.1.0), *cli*(v.3.6.4), *mvtnorm*(v.1.3-3), *crayon*(v.1.5.3), *rmarkdown*(v.2.29), *generics*(v.0.1.3), *rstudioapi*(v.0.17.1), *tzdb*(v.0.5.0), *splines*(v.4.4.3), *parallel*(v.4.4.3), *base64enc*(v.0.1-3), *vctrs*(v.0.6.5), *Matrix*(v.1.7-3), *bookdown*(v.0.4.2), *hms*(v.1.1.3), *bit64*(v.4.6.0-1), *rstatix*(v.0.7.2), *Formula*(v.1.2-5), *htmlTable*(v.2.4.3), *systemfonts*(v.1.2.1), *glue*(v.1.8.0), *admisc*(v.0.37), *cowplot*(v.1.1.3), *stringi*(v.1.8.4), *gtable*(v.0.3.6), *munsell*(v.0.5.1), *pillar*(v.1.10.1), *htmltools*(v.0.5.8.1), *R6*(v.2.6.1), *vroom*(v.1.6.5), *evaluate*(v.1.0.3), *lattice*(v.0.22-6), *cards*(v.0.5.1), *backports*(v.1.5.0), *broom*(v.1.0.7), *Rcpp*(v.1.0.14), *svglite*(v.2.1.3), *gridExtra*(v.2.3), *nlme*(v.3.1-167), *checkmate*(v.2.3.2), *xfun*(v.0.51) and *pkgconfig*(v.2.0.3)

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