

2_descriptives

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Helper functions

```
# Color palettes consistent across plots

pal_target <- c(
  "self"      = "#E15759",
  "climate"   = "#59A14F",
  "prosocial" = "#4E79A7"
)

pal_group <- c(
  "control"      = "#4E79A7",
  "positive_norm" = "#59A14F",
  "negative_norm" = "#E15759"
)

pd <- position_dodge(width = 0.7)

group_labels <- c(
  "control"      = "Control Group",
  "positive_norm" = "Positive Norm",
  "negative_norm" = "Negative Norm"
)

# Function to extract key fit indices
fit_table <- function(fit) {
  data.frame(
    ChiSq = fitMeasures(fit, "chisq"),
    df    = fitMeasures(fit, "df"),
    CFI    = fitMeasures(fit, "cfi"),
    TLI    = fitMeasures(fit, "tli"),
    RMSEA = fitMeasures(fit, "rmsea"),
    SRMR  = fitMeasures(fit, "srmr")
  )
}
```

Descriptive Statistics

1. Sample Characteristics

Currently we do not have demographic information, thus the r chunk below does not run. Should any of this information be available in the future, the following entries should be removed from the r chunk below.

```
include = FALSE, eval = FALSE
```

2. Primary Outcome: Choice Behaviour

```
# Overall choice rates
df_long |>
  summarise(
    mean_choice = mean(choice, na.rm = TRUE),
    sd_choice = sd(choice, na.rm = TRUE)
  )
```

```
## # A tibble: 1 x 2
##   mean_choice sd_choice
##       <dbl>    <dbl>
## 1      0.924      0.266
```

```
# By target type
df_long |>
  group_by(target) |>
  summarise(
    mean_choice = mean(choice, na.rm = TRUE),
    sd_choice = sd(choice, na.rm = TRUE),
    n_trials = n()
  )
```

```
## # A tibble: 3 x 4
##   target    mean_choice sd_choice n_trials
##   <fct>         <dbl>    <dbl>    <int>
## 1 self           0.933      0.251     1968
## 2 climate        0.922      0.269     1968
## 3 prosocial      0.916      0.277     1968
```

```
# By group and block (most important!)
df_long |>
  group_by(group, block) |>
  summarise(
    mean_choice = mean(choice, na.rm = TRUE),
    sd_choice = sd(choice, na.rm = TRUE),
    n_trials = n()
  )
```

```
## # A tibble: 6 x 5
## # Groups:   group [3]
```

```
##   group      block mean_choice sd_choice n_trials
##   <fct>      <fct>      <dbl>      <dbl>      <int>
## 1 control    pre        0.898        0.303       1008
## 2 control    post       0.929        0.257       1008
## 3 positive_norm pre      0.907        0.290        990
## 4 positive_norm post     0.944        0.229        990
## 5 negative_norm pre      0.923        0.266        954
## 6 negative_norm post     0.941        0.235        954
```

```
# By all three factors (for comprehensive table)
```

```
df_long |>
  group_by(target, group, block) |>
  summarise(
    M = mean(choice, na.rm = TRUE),
    SD = sd(choice, na.rm = TRUE)
  ) |>
  arrange(target, group, block)
```

```
## # A tibble: 18 x 5
## # Groups:   target, group [9]
##   target  group      block      M      SD
##   <fct>   <fct>      <fct> <dbl> <dbl>
## 1 self    control    pre    0.896 0.306
## 2 self    control    post   0.934 0.248
## 3 self    positive_norm pre    0.927 0.260
## 4 self    positive_norm post   0.975 0.155
## 5 self    negative_norm pre    0.928 0.259
## 6 self    negative_norm post   0.937 0.243
## 7 climate control    pre    0.893 0.310
## 8 climate control    post   0.924 0.265
## 9 climate positive_norm pre    0.918 0.275
## 10 climate positive_norm post   0.926 0.262
## 11 climate negative_norm pre    0.925 0.265
## 12 climate negative_norm post   0.947 0.225
## 13 prosocial control    pre    0.905 0.294
## 14 prosocial control    post   0.928 0.259
## 15 prosocial positive_norm pre    0.876 0.330
## 16 prosocial positive_norm post   0.932 0.252
## 17 prosocial negative_norm pre    0.918 0.274
## 18 prosocial negative_norm post   0.940 0.237
```

3. Task Controls: Reward and Effort

```
# Choice rates by reward level
```

```
df_long |>
  group_by(reward) |>
  summarise(
    mean_choice = mean(choice, na.rm = TRUE),
    sd_choice = sd(choice, na.rm = TRUE)
  )
```

```
## # A tibble: 3 x 3
```

```
##   reward    mean_choice sd_choice
##   <fct>      <dbl>      <dbl>
## 1 2 points    0.861      0.346
## 2 6 points    0.95       0.218
## 3 10 points   0.960      0.197
```

```
# Choice rates by effort level
df_long |>
  group_by(effort) |>
  summarise(
    mean_choice = mean(choice, na.rm = TRUE),
    sd_choice = sd(choice, na.rm = TRUE)
  )
```

```
## # A tibble: 2 x 3
##   effort mean_choice sd_choice
##   <fct>      <dbl>      <dbl>
## 1 40%       0.959      0.199
## 2 90%       0.889      0.315
```

```
# Reward × Effort interaction pattern
df_long |>
  group_by(reward, effort) |>
  summarise(
    mean_choice = mean(choice, na.rm = TRUE),
    sd_choice = sd(choice, na.rm = TRUE)
  )
```

```
## # A tibble: 6 x 4
## # Groups:   reward [3]
##   reward    effort mean_choice sd_choice
##   <fct>    <fct>      <dbl>      <dbl>
## 1 2 points 40%       0.935      0.247
## 2 2 points 90%       0.787      0.409
## 3 6 points 40%       0.966      0.180
## 4 6 points 90%       0.934      0.249
## 5 10 points 40%      0.974      0.158
## 6 10 points 90%      0.945      0.229
```

4. Moderator Variables

```
sus_scores <- df_wide |>
  select(starts_with("SUS_")) |>
  mutate(across(everything(), as.numeric))

sus_scores
```

```
##   SUS_1 SUS_2 SUS_3 SUS_4 SUS_5 SUS_6 SUS_7 SUS_8
## 1     1     3     1     5     1     3     3     1
## 2     1     4     1     5     1     2     1     1
```

## 3	3	5	3	5	3	5	5	3
## 4	1	3	2	4	2	2	1	1
## 5	3	3	2	4	2	3	3	4
## 6	3	2	3	5	5	4	5	3
## 7	3	4	4	5	3	4	3	1
## 8	1	5	2	3	1	2	2	1
## 9	2	4	4	4	3	4	5	1
## 10	NA	NA	NA	NA	NA	NA	NA	NA
## 11	3	2	2	4	3	3	4	2
## 12	NA	NA	NA	NA	NA	NA	NA	NA
## 13	2	1	2	3	1	1	2	3
## 14	3	2	3	3	3	3	2	2
## 15	2	2	1	2	2	3	2	1
## 16	1	2	1	3	2	2	1	1
## 17	NA	NA	NA	NA	NA	NA	NA	NA
## 18	1	1	1	1	1	1	1	1
## 19	2	2	1	4	2	3	2	2
## 20	1	1	1	1	1	1	1	1
## 21	3	3	3	3	3	3	3	3
## 22	3	2	1	4	4	3	4	2
## 23	NA	NA	NA	NA	NA	NA	NA	NA
## 24	3	3	2	3	4	2	3	3
## 25	1	3	2	3	2	2	3	4
## 26	3	3	3	4	3	3	2	4
## 27	2	4	2	4	1	3	1	1
## 28	3	4	2	3	1	2	1	3
## 29	3	4	1	3	1	2	5	1
## 30	3	3	3	3	2	3	4	3
## 31	2	2	2	5	2	3	2	2
## 32	2	4	2	3	2	3	3	2
## 33	5	5	4	5	1	3	5	1
## 34	3	2	2	2	2	2	1	1
## 35	3	4	2	1	2	3	3	2
## 36	4	5	5	2	5	5	4	3
## 37	2	2	2	2	2	2	2	2
## 38	2	3	1	3	1	3	1	1
## 39	1	1	1	3	1	1	3	1
## 40	3	3	3	3	3	3	3	3
## 41	2	2	2	4	2	2	3	2
## 42	3	3	3	4	2	4	3	3
## 43	2	3	2	4	2	4	1	3
## 44	2	4	1	4	1	1	1	1
## 45	3	3	3	4	3	5	3	3
## 46	5	1	5	5	5	5	5	5
## 47	2	1	3	5	3	5	1	2
## 48	2	2	1	2	1	1	3	1
## 49	1	1	1	4	1	1	1	2
## 50	4	3	4	3	4	3	2	2
## 51	1	1	1	1	1	1	1	1
## 52	1	3	1	4	1	1	2	1
## 53	1	3	1	3	1	1	1	1
## 54	1	1	1	3	1	1	1	1
## 55	2	2	2	4	2	2	2	1
## 56	1	1	1	1	1	1	1	1

## 57	1	1	1	1	1	1	1	1
## 58	1	3	2	3	2	2	3	4
## 59	1	2	2	3	1	1	1	2
## 60	2	2	2	3	3	2	3	2
## 61	2	4	4	3	4	3	4	3
## 62	2	1	2	1	1	2	2	1
## 63	2	2	2	4	2	2	1	1
## 64	3	4	3	4	3	3	4	2
## 65	3	3	3	4	4	5	5	5
## 66	4	2	4	3	4	4	4	3
## 67	1	5	1	4	1	2	1	1
## 68	NA	NA	NA	NA	NA	NA	NA	NA
## 69	2	3	2	4	2	2	2	1
## 70	2	1	1	1	3	3	2	2
## 71	2	3	5	4	1	1	5	5
## 72	2	3	2	2	3	2	2	1
## 73	3	2	3	4	3	2	3	1
## 74	4	3	3	5	3	2	2	1
## 75	3	2	2	2	1	2	2	1
## 76	4	3	5	5	5	4	5	1
## 77	5	3	5	4	5	4	5	2
## 78	5	5	3	5	4	2	3	3
## 79	3	3	1	3	1	1	1	1
## 80	2	1	2	2	1	1	3	1
## 81	2	2	2	2	1	2	2	1
## 82	3	3	4	4	4	5	5	3
## 83	2	3	5	4	5	3	5	4
## 84	3	4	4	5	4	5	4	4
## 85	3	3	4	3	4	3	3	3
## 86	2	3	2	3	2	1	2	1
## 87	2	4	2	4	2	4	4	3
## 88	2	4	1	3	1	2	1	2
## 89	2	2	3	4	4	3	4	3
## 90	3	2	1	4	2	2	4	2
## 91	3	2	3	2	4	5	3	4
## 92	NA	NA	NA	NA	NA	NA	NA	NA
## 93	3	3	3	3	3	3	3	1
## 94	2	3	2	3	2	4	3	2
## 95	2	3	2	4	3	1	2	2
## 96	1	1	1	1	1	1	2	1
## 97	1	1	1	1	1	1	1	1
## 98	3	4	3	4	2	2	3	1
## 99	1	1	2	2	4	3	2	3
## 100	3	4	3	4	3	2	2	2
## 101	3	4	3	5	3	3	4	3
## 102	3	3	2	3	3	3	3	3
## 103	2	3	2	4	2	2	2	1
## 104	2	3	2	1	2	3	1	1
## 105	2	5	4	5	5	4	5	1
## 106	5	4	5	3	5	5	5	5
## 107	2	2	2	3	3	2	3	2
## 108	1	1	1	1	1	1	1	1
## 109	2	2	1	1	2	3	2	1
## 110	3	2	1	1	2	1	1	1

## 111	2	3	2	4	2	2	1	1
## 112	2	3	2	3	1	3	1	1
## 113	1	4	1	5	1	3	1	1
## 114	1	3	1	4	2	2	1	1
## 115	4	4	4	4	4	4	4	2
## 116	2	2	1	2	2	2	3	1
## 117	4	4	4	4	4	4	3	3
## 118	2	1	1	3	2	2	1	1
## 119	3	3	3	3	3	3	3	3
## 120	2	2	2	3	2	3	2	4
## 121	4	3	3	3	3	2	3	2
## 122	2	2	4	3	4	3	3	3
## 123	2	2	2	4	3	4	3	4
## 124	2	2	3	3	4	4	4	3
## 125	2	3	2	1	1	2	3	2
## 126	4	3	5	3	5	4	5	5
## 127	1	3	3	5	4	3	4	3
## 128	1	1	1	1	1	1	1	1
## 129	1	3	2	5	1	1	3	1
## 130	2	1	1	2	2	2	2	1
## 131	3	4	3	3	3	2	3	3
## 132	1	3	1	3	2	1	4	4
## 133	1	5	4	4	3	3	3	4
## 134	3	3	4	3	4	4	3	4
## 135	3	3	3	4	4	1	1	3
## 136	3	3	1	4	1	1	1	1
## 137	3	4	2	5	4	2	4	3
## 138	1	2	1	2	1	1	2	1
## 139	3	4	3	3	3	2	4	3
## 140	2	3	1	5	1	3	2	3
## 141	3	3	1	1	2	2	1	1
## 142	5	5	4	5	4	5	5	3
## 143	2	4	3	5	3	5	3	5
## 144	3	5	1	5	1	3	2	1
## 145	3	3	4	4	3	3	4	3
## 146	4	5	1	3	1	2	4	5
## 147	2	1	1	1	1	1	1	1
## 148	5	4	2	4	3	5	4	3
## 149	3	5	3	1	3	3	3	1
## 150	2	3	2	2	2	2	3	3
## 151	2	2	2	4	2	2	2	5
## 152	2	2	1	3	2	1	1	2
## 153	2	4	3	4	3	3	3	3
## 154	2	3	3	4	2	2	1	2
## 155	4	3	3	3	3	3	3	3
## 156	2	3	2	3	2	3	2	2
## 157	2	2	1	4	2	3	3	1
## 158	4	3	4	3	4	2	5	3
## 159	1	2	2	4	1	2	1	1
## 160	1	1	1	1	1	1	1	1
## 161	2	2	1	4	1	1	1	2
## 162	4	3	2	5	3	4	2	3
## 163	1	1	1	1	1	1	1	1
## 164	4	3	3	5	4	3	3	2

```
str(sus_scores)
```

```
## 'data.frame': 164 obs. of 8 variables:  
## $ SUS_1: num 1 1 3 1 3 3 3 1 2 NA ...  
## $ SUS_2: num 3 4 5 3 3 2 4 5 4 NA ...  
## $ SUS_3: num 1 1 3 2 2 3 4 2 4 NA ...  
## $ SUS_4: num 5 5 5 4 4 5 5 3 4 NA ...  
## $ SUS_5: num 1 1 3 2 2 5 3 1 3 NA ...  
## $ SUS_6: num 3 2 5 2 3 4 4 2 4 NA ...  
## $ SUS_7: num 3 1 5 1 3 5 3 2 5 NA ...  
## $ SUS_8: num 1 1 3 1 4 3 1 1 1 NA ...
```

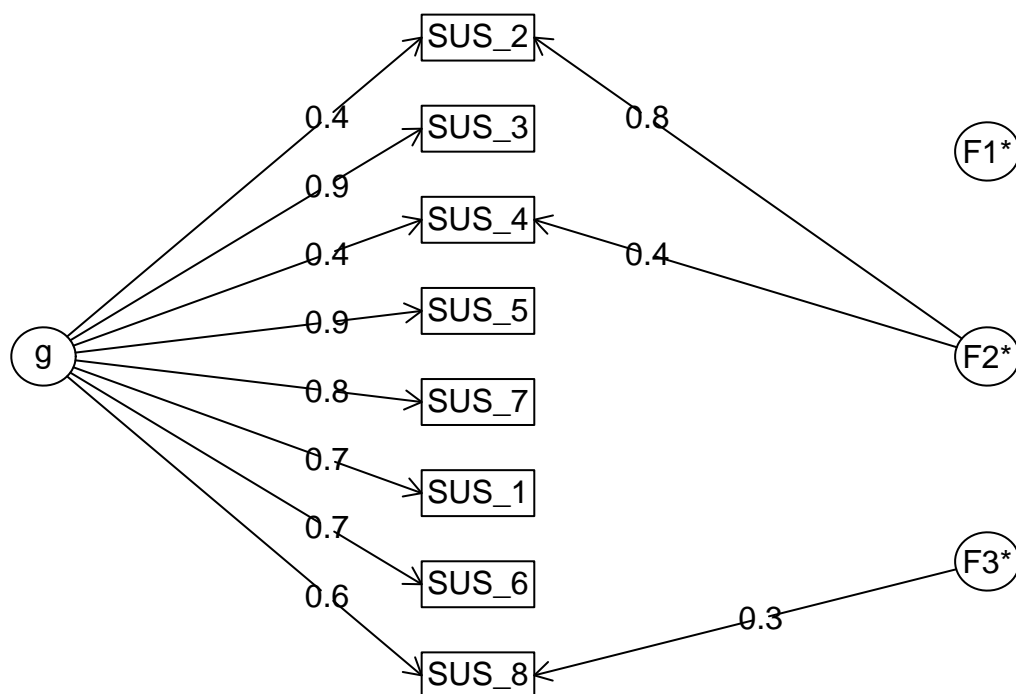
```
# Reliability
```

```
psych::alpha(sus_scores, use = "pairwise")$total# alpha
```

```
## raw_alpha std.alpha G6(smc) average_r S/N ase mean sd  
## 0.8745036 0.8745255 0.8795407 0.4655888 6.969746 0.01469615 2.548259 0.8676012  
## median_r  
## 0.4729983
```

```
psych::omega(sus_scores, use = "pairwise")$omega.tot # omega total
```

Omega



```
## [1] 0.9086112
```



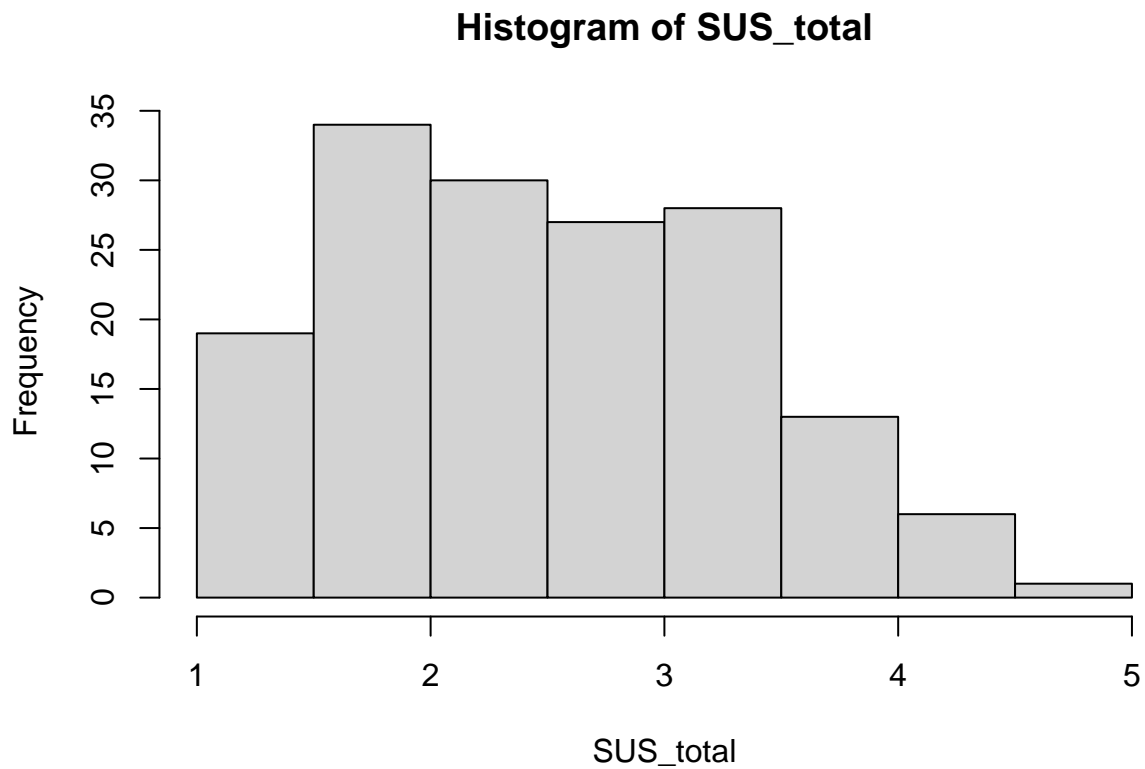
```
# Total score
```

```
SUS_total <- rowMeans(sus_scores, na.rm=TRUE)
```

```
describe(SUS_total) # descriptives for SUS
```

```
##      vars   n mean   sd median trimmed  mad min  max range skew kurtosis   se  
## X1      1 158 2.55 0.87   2.5   2.54 0.93   1 4.62  3.62 0.14   -0.67 0.07
```

```
hist(SUS_total)
```



Confirmatory Factor Analysis

One factor model

```
# Single factor model
```

```
model <- '  
SUS =~ SUS_1 + SUS_2 + SUS_3 + SUS_4 + SUS_5 + SUS_6 + SUS_7 + SUS_8  
'
```

```
fit1 <- cfa(
  model,
  data = sus_scores,
  std.lv = TRUE,
  missing = "fiml"
)

summary(fit1, fit.measures = TRUE, standardized = TRUE)
```

```
## lavaan 0.6-20 ended normally after 17 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters      24
##
##                               Used      Total
##      Number of observations          158      164
##      Number of missing patterns        1
##
## Model Test User Model:
##
##      Test statistic                  51.300
##      Degrees of freedom                20
##      P-value (Chi-square)             0.000
##
## Model Test Baseline Model:
##
##      Test statistic                  609.286
##      Degrees of freedom                28
##      P-value                          0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.946
##      Tucker-Lewis Index (TLI)        0.925
##
##      Robust Comparative Fit Index (CFI) 0.946
##      Robust Tucker-Lewis Index (TLI)    0.925
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -1725.164
##      Loglikelihood unrestricted model (H1) -1699.514
##
##      Akaike (AIC)                      3498.328
##      Bayesian (BIC)                     3571.831
##      Sample-size adjusted Bayesian (SABIC) 3495.859
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                             0.100
```

```

## 90 Percent confidence interval - lower      0.066
## 90 Percent confidence interval - upper      0.134
## P-value H_0: RMSEA <= 0.050                0.009
## P-value H_0: RMSEA >= 0.080                0.845
##
## Robust RMSEA                                0.100
## 90 Percent confidence interval - lower      0.066
## 90 Percent confidence interval - upper      0.134
## P-value H_0: Robust RMSEA <= 0.050         0.009
## P-value H_0: Robust RMSEA >= 0.080         0.845
##
## Standardized Root Mean Square Residual:
##
## SRMR                                         0.053
##
## Parameter Estimates:
##
## Standard errors                                Standard
## Information                                    Observed
## Observed information based on                    Hessian
##
## Latent Variables:
##
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SUS =~
## SUS_1      0.727   0.076   9.585   0.000   0.727   0.691
## SUS_2      0.498   0.089   5.566   0.000   0.498   0.442
## SUS_3      1.009   0.076  13.341   0.000   1.009   0.867
## SUS_4      0.544   0.097   5.616   0.000   0.544   0.444
## SUS_5      1.040   0.080  12.963   0.000   1.040   0.851
## SUS_6      0.886   0.083  10.688   0.000   0.886   0.749
## SUS_7      1.007   0.090  11.202   0.000   1.007   0.773
## SUS_8      0.726   0.089   8.159   0.000   0.726   0.610
##
## Intercepts:
##
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .SUS_1      2.380   0.084  28.405   0.000   2.380   2.260
## .SUS_2      2.785   0.090  31.060   0.000   2.785   2.471
## .SUS_3      2.285   0.093  24.667   0.000   2.285   1.962
## .SUS_4      3.266   0.097  33.529   0.000   3.266   2.667
## .SUS_5      2.392   0.097  24.623   0.000   2.392   1.959
## .SUS_6      2.551   0.094  27.103   0.000   2.551   2.156
## .SUS_7      2.595   0.104  25.041   0.000   2.595   1.992
## .SUS_8      2.133   0.095  22.506   0.000   2.133   1.791
##
## Variances:
##
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .SUS_1      0.580   0.072   8.091   0.000   0.580   0.523
## .SUS_2      1.022   0.118   8.648   0.000   1.022   0.805
## .SUS_3      0.337   0.054   6.214   0.000   0.337   0.248
## .SUS_4      1.203   0.139   8.663   0.000   1.203   0.803
## .SUS_5      0.410   0.063   6.547   0.000   0.410   0.275
## .SUS_6      0.615   0.080   7.719   0.000   0.615   0.439
## .SUS_7      0.682   0.090   7.560   0.000   0.682   0.402
## .SUS_8      0.892   0.107   8.370   0.000   0.892   0.628

```

```
##      SUS      1.000      1.000      1.000
```

Two factor model

```
# Two factor model

model2 <- '
  Anxiety =~ SUS_1 + SUS_3 + SUS_5 + SUS_7
  Selfesteem =~ SUS_2 + SUS_4 + SUS_6 + SUS_8
'

fit2 <- cfa(
  model2,
  data = sus_scores,
  std.lv = TRUE,
  missing = "fiml"
)

summary(fit2, fit.measures = TRUE, standardized = TRUE)
```

```
## lavaan 0.6-20 ended normally after 20 iterations
##
##      Estimator      ML
##      Optimization method      NLMINB
##      Number of model parameters      25
##
##      Used      Total
##      Number of observations      158      164
##      Number of missing patterns      1
##
## Model Test User Model:
##
##      Test statistic      45.589
##      Degrees of freedom      19
##      P-value (Chi-square)      0.001
##
## Model Test Baseline Model:
##
##      Test statistic      609.286
##      Degrees of freedom      28
##      P-value      0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.954
##      Tucker-Lewis Index (TLI)      0.933
##
##      Robust Comparative Fit Index (CFI)      0.954
##      Robust Tucker-Lewis Index (TLI)      0.933
```

```

##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -1722.309
##   Loglikelihood unrestricted model (H1)      -1699.514
##
##   Akaike (AIC)                            3494.617
##   Bayesian (BIC)                          3571.182
##   Sample-size adjusted Bayesian (SABIC)     3492.045
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                    0.094
##   90 Percent confidence interval - lower    0.059
##   90 Percent confidence interval - upper    0.129
##   P-value H_0: RMSEA <= 0.050             0.021
##   P-value H_0: RMSEA >= 0.080             0.768
##
##   Robust RMSEA                            0.094
##   90 Percent confidence interval - lower    0.059
##   90 Percent confidence interval - upper    0.129
##   P-value H_0: Robust RMSEA <= 0.050       0.021
##   P-value H_0: Robust RMSEA >= 0.080       0.768
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                    0.049
##
## Parameter Estimates:
##
##   Standard errors                        Standard
##   Information                          Observed
##   Observed information based on         Hessian
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   Anxiety =~
##     SUS_1           0.728    0.076    9.588    0.000    0.728    0.692
##     SUS_3           1.018    0.075   13.495    0.000    1.018    0.874
##     SUS_5           1.049    0.080   13.108    0.000    1.049    0.859
##     SUS_7           1.003    0.090   11.113    0.000    1.003    0.770
##   Selfesteem =~
##     SUS_2           0.537    0.092    5.845    0.000    0.537    0.477
##     SUS_4           0.601    0.100    6.025    0.000    0.601    0.491
##     SUS_6           0.945    0.086   11.045    0.000    0.945    0.799
##     SUS_8           0.744    0.091    8.133    0.000    0.744    0.625
##
## Covariances:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   Anxiety ~~
##     Selfesteem       0.914    0.039   23.326    0.000    0.914    0.914
##
## Intercepts:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all

```

```
##      .SUS_1      2.380    0.084   28.405    0.000    2.380    2.260
##      .SUS_3      2.285    0.093   24.667    0.000    2.285    1.962
##      .SUS_5      2.392    0.097   24.623    0.000    2.392    1.959
##      .SUS_7      2.595    0.104   25.041    0.000    2.595    1.992
##      .SUS_2      2.785    0.090   31.060    0.000    2.785    2.471
##      .SUS_4      3.266    0.097   33.529    0.000    3.266    2.667
##      .SUS_6      2.551    0.094   27.103    0.000    2.551    2.156
##      .SUS_8      2.133    0.095   22.506    0.000    2.133    1.791
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .SUS_1      0.578    0.072    8.057    0.000    0.578    0.521
##      .SUS_3      0.319    0.054    5.904    0.000    0.319    0.235
##      .SUS_5      0.392    0.062    6.292    0.000    0.392    0.263
##      .SUS_7      0.690    0.092    7.521    0.000    0.690    0.407
##      .SUS_2      0.981    0.117    8.378    0.000    0.981    0.773
##      .SUS_4      1.137    0.137    8.312    0.000    1.137    0.759
##      .SUS_6      0.506    0.089    5.711    0.000    0.506    0.362
##      .SUS_8      0.866    0.110    7.901    0.000    0.866    0.610
##      Anxiety      1.000
##      Selfesteem    1.000
```

Fit Measures

```
fit_table(fit1)
```

```
##      ChiSq df      CFI      TLI      RMSEA      SRMR
## chisq 51.30013 20 0.9461536 0.9246151 0.09952439 0.05298635
```

```
fit_table(fit2)
```

```
##      ChiSq df      CFI      TLI      RMSEA      SRMR
## chisq 45.58885 19 0.9542586 0.9325916 0.09411187 0.04908875
```

5. Ceiling Effects

```
# By participant overall
ceiling_participants <- df_long |>
  group_by(ppn) |>
  summarise(
    prop_high_effort = mean(choice, na.rm = TRUE)
  ) |>
  summarise(
    at_90 = sum(prop_high_effort >= 0.90),
    pct_90 = mean(prop_high_effort >= 0.90) * 100,
    at_95 = sum(prop_high_effort >= 0.95),
    pct_95 = mean(prop_high_effort >= 0.95) * 100,
    at_100 = sum(prop_high_effort == 1.00),
    pct_100 = mean(prop_high_effort == 1.00) * 100
```

```
)

print(ceiling_participants)

## # A tibble: 1 x 6
##   at_90 pct_90 at_95 pct_95 at_100 pct_100
##   <int> <dbl> <int> <dbl> <int> <dbl>
## 1   118   72.0   84   51.2   52   31.7

# By participant and block
ceiling_by_block <- df_long |>
  group_by(ppn, block) |>
  summarise(
    prop_high_effort = mean(choice, na.rm = TRUE),
    .groups = "drop"
  ) |>
  group_by(block) |>
  summarise(
    n_at_90 = sum(prop_high_effort >= 0.90),
    pct_at_90 = mean(prop_high_effort >= 0.90) * 100,
    n_at_95 = sum(prop_high_effort >= 0.95),
    pct_at_95 = mean(prop_high_effort >= 0.95) * 100,
    n_at_100 = sum(prop_high_effort == 1.00),
    pct_at_100 = mean(prop_high_effort == 1.00) * 100
  )

print(ceiling_by_block)
```

```
## # A tibble: 2 x 7
##   block n_at_90 pct_at_90 n_at_95 pct_at_95 n_at_100 pct_at_100
##   <fct> <int> <dbl> <int> <dbl> <int> <dbl>
## 1 pre     100   61.0   59   36.0   59   36.0
## 2 post     NA    NA    NA    NA    NA    NA
```

```
# Calculate proportion of high-effort choices per participant
participant_props <- df_long |>
  group_by(ppn) |>
  summarise(
    prop_high_effort = mean(choice, na.rm = TRUE)
  )

# Descriptives
summary(participant_props$prop_high_effort)
```

```
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.4444 0.8889 0.9722 0.9238 1.0000 1.0000
```

```
quantile(participant_props$prop_high_effort, probs = c(0.25, 0.5, 0.75))
```

```
##      25%      50%      75%
## 0.888889 0.972222 1.000000
```

```
# How many chose high effort 100% of the time?
sum(participant_props$prop_high_effort == 1.0)
```

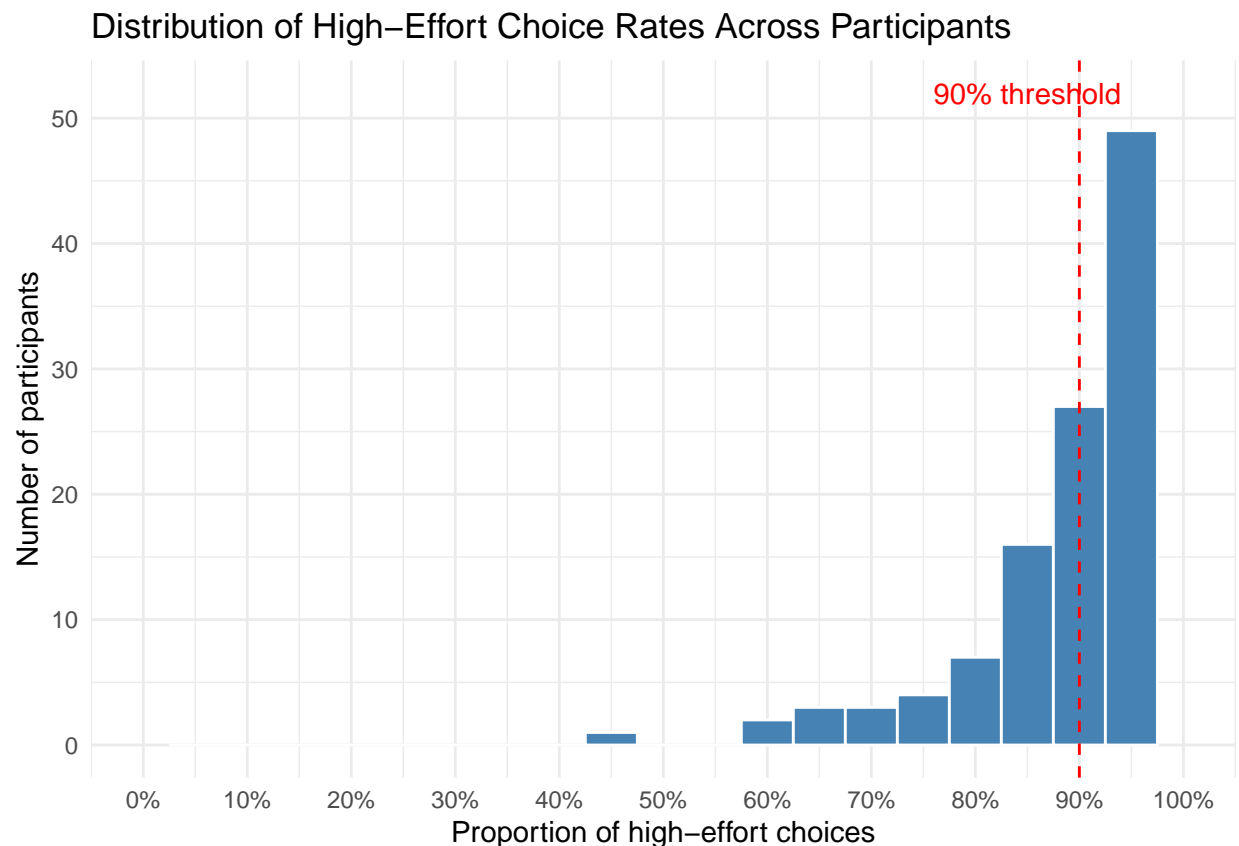
```
## [1] 52
```

```
mean(participant_props$prop_high_effort == 1.0) * 100
```

```
## [1] 31.70732
```

```
# Histogram
```

```
ggplot(participant_props, aes(x = prop_high_effort)) +
  geom_histogram(binwidth = 0.05, fill = "steelblue", color = "white") +
  scale_x_continuous(limits = c(0, 1),
                     breaks = seq(0, 1, 0.1),
                     labels = scales::percent) +
  labs(x = "Proportion of high-effort choices",
       y = "Number of participants",
       title = "Distribution of High-Effort Choice Rates Across Participants") +
  theme_minimal() +
  geom_vline(xintercept = 0.90, linetype = "dashed", color = "red") +
  annotate("text", x = 0.85, y = max(table(cut(participant_props$prop_high_effort, breaks = 20))),
         label = "90% threshold", color = "red")
```




```

# Standard deviation of choices (within-person)
within_person_variability <- df_long|>
  group_by(ppn)|>
  summarise(
    sd_choice = sd(choice, na.rm = TRUE),
    var_choice = var(choice, na.rm = TRUE)
  )|>
  summarise(
    mean_sd = mean(sd_choice, na.rm = TRUE),
    median_sd = median(sd_choice, na.rm = TRUE),
    n_zero_var = sum(sd_choice == 0, na.rm = TRUE),
    pct_zero_var = mean(sd_choice == 0, na.rm = TRUE) * 100
  )

print(within_person_variability)

```

```

## # A tibble: 1 x 4
##   mean_sd median_sd n_zero_var pct_zero_var
##   <dbl>      <dbl>      <int>      <dbl>
## 1   0.195      0.167         52       31.7

```

```

# Ceiling by experimental conditions
ceiling_by_group <- df_long|>
  group_by(ppn, group)|>
  summarise(
    prop_high_effort = mean(choice, na.rm = TRUE),
    .groups = "drop"
  )|>
  group_by(group)|>
  summarise(
    n_at_90 = sum(prop_high_effort >= 0.90),
    pct_at_90 = mean(prop_high_effort >= 0.90) * 100,
    mean_prop = mean(prop_high_effort),
    sd_prop = sd(prop_high_effort),
    median_prop = median(prop_high_effort)
  )

print(ceiling_by_group)

```

```

## # A tibble: 3 x 6
##   group      n_at_90 pct_at_90 mean_prop sd_prop median_prop
##   <fct>      <int>      <dbl>      <dbl>  <dbl>      <dbl>
## 1 control         36      64.3      0.913  0.107      0.972
## 2 positive_norm    43      78.2      0.926  0.0990     0.972
## 3 negative_norm    39      73.6      0.932  0.0840     0.972

```

```

# table
ceiling_summary <- df_long |>
  group_by(ppn)|>
  summarise(
    prop = mean(choice, na.rm = TRUE),
    sd = sd(choice, na.rm = TRUE)
  )

```

```

)|>
summarise(
  mean = mean(prop),
  sd = sd(prop),
  median = median(prop),
  q25 = quantile(prop, 0.25),
  q75 = quantile(prop, 0.75),
  min = min(prop),
  max = max(prop),
  n_90 = sum(prop >= 0.90),
  pct_90 = mean(prop >= 0.90) * 100,
  n_95 = sum(prop >= 0.95),
  pct_95 = mean(prop >= 0.95) * 100,
  n_100 = sum(prop == 1.00),
  pct_100 = mean(prop == 1.00) * 100,
  mean_within_sd = mean(sd, na.rm = TRUE),
  n_zero_var = sum(sd == 0, na.rm = TRUE),
  pct_zero_var = mean(sd == 0, na.rm = TRUE) * 100
)

print(ceiling_summary)

```

```

## # A tibble: 1 x 16
##   mean      sd median  q25   q75   min   max  n_90 pct_90  n_95 pct_95 n_100
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <int> <dbl> <int> <dbl> <int>
## 1 0.924 0.0970  0.972 0.889    1 0.444    1   118   72.0    84   51.2    52
## # i 4 more variables: pct_100 <dbl>, mean_within_sd <dbl>, n_zero_var <int>,
## #   pct_zero_var <dbl>

```

5. Missing Data Summary

1) Helper functions

```

# Color palettes consistent across plots

pal_target <- c(
  "self"      = "#E15759",
  "climate"   = "#59A14F",
  "prosocial" = "#4E79A7"
)

pal_group <- c(
  "control"    = "#4E79A7",
  "positive_norm" = "#59A14F",
  "negative_norm" = "#E15759"
)

pd <- position_dodge(width = 0.7)

```

```
group_labels <- c(
  "control" = "Control Group",
  "positive_norm" = "Positive Norm",
  "negative_norm" = "Negative Norm"
)
```

Susceptibility

```
susceptibility_descriptives <- df_long |>
  summarise(
    M = mean(susceptibility, na.rm = TRUE),
    SD = sd(susceptibility, na.rm = TRUE),
    Min = min(susceptibility, na.rm = TRUE),
    Max = max(susceptibility, na.rm = TRUE)
  )
```

```
susceptibility_descriptives
```

```
## # A tibble: 1 x 4
##       M     SD   Min   Max
##   <dbl> <dbl> <dbl> <dbl>
## 1  2.54 0.852     1  4.62
```

Visualizations

a) Reward \times Effort interaction

```
plot_a_data <- df_long |>
  group_by(reward, effort) |>
  summarise(p = mean(choice == 1, na.rm = TRUE), .groups = "drop")

reward_effort_plot <- plot_a_data |>
  ggplot(aes(x = reward, y = p, color = effort, group = effort)) +
  geom_point(size = 3) +
  geom_line(size = 1) +
  scale_color_manual(values = c(
    "40%" = "#E15759",
    "90%" = "#4E79A7"
  )) +
  scale_y_continuous(limits = c(0, 1)) +
  labs(
    x = "Reward",
    y = "Proportion of High-Effort Choices",
    color = "Effort"
  ) +
  theme_bw()
```

```
ggsave("figures/descriptives/reward_effort_plot.png",
       plot = reward_effort_plot,
       width = 7, height = 5, dpi = 300)
```

b) Target × Block × Group

```
plot_b_data <- df_long |>
  group_by(group, block, target) |>
  summarise(
    p_choice = mean(choice == 1, na.rm = TRUE),
    n         = sum(!is.na(choice)),
    .groups = "drop"
  )

target_block_group_plot <- plot_b_data |>
  ggplot(aes(x = block,
             y = p_choice,
             color = target,
             group = target)) +
  geom_point(size = 3) +
  geom_line(size = 1) +
  facet_wrap(~ group, labeller = labeller(group = group_labels)) +
  labs(
    x      = "Block",
    y      = "Proportion of High-Effort Choices",
    color  = "Target"
  ) +
  scale_y_continuous(limits = c(0, 1)) +
  scale_color_manual(values = pal_target) +
  theme_bw() +
  theme(
    legend.position = "top",
    legend.title    = element_blank()
  )

ggsave("figures/descriptives/target_block_group_plot.png",
       plot = target_block_group_plot,
       width = 7, height = 5, dpi = 300)
```