

waveley_attempt

Waveley Qiu (wq2162)

2022-04-30

Athletic Identity

First, let's select the variables we are interested in.

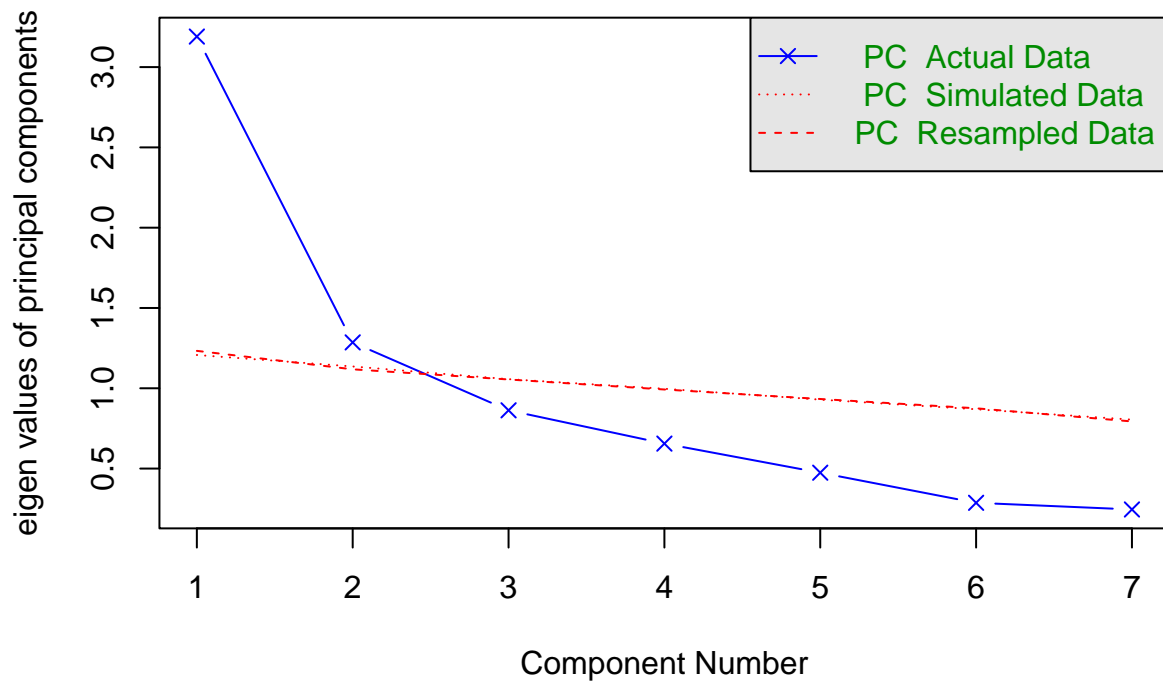
```
athletic_identity <- c("cnsdr_ath", "sprt_goals", "frnds_ath", "sprt_impt", "think_sprt", "bad_sprt", "o  
athletic_identity_numeric <- athletes[,athletic_identity] %>% map_df(., as.numeric)  
athletic_identity_matrix <- athletic_identity_numeric %>% as.matrix()
```

Polychoric Correlations

Now, let us determine the number of factors that might underlie these variables.

```
athlete_parallel <- fa.parallel(athletic_identity_matrix, cor = "poly", fa = "pc")
```

Parallel Analysis Scree Plots



```
## Parallel analysis suggests that the number of factors = NA and the number of components = 2
athlete_parallel$pc.values
```

```
## [1] 3.1901693 1.2855443 0.8626912 0.6554703 0.4741985 0.2866577 0.2452687
```

PCA indicates that two factors underlie these variables.

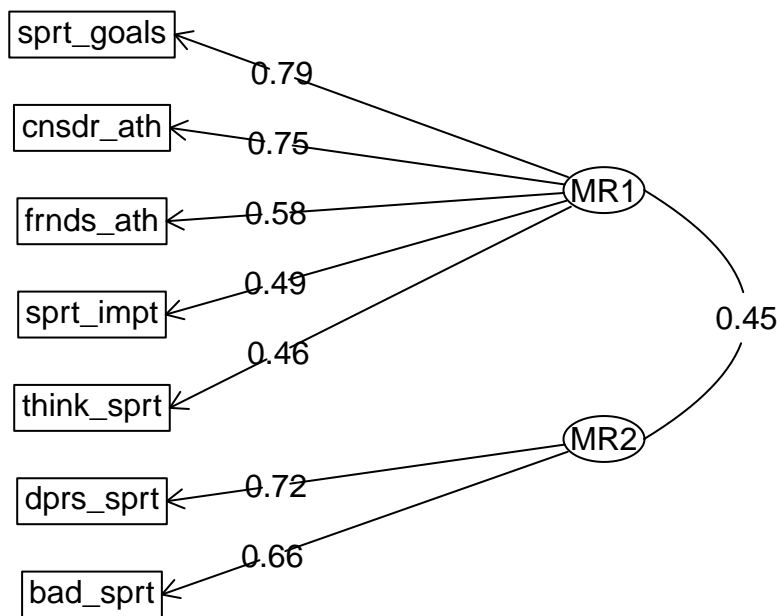
EFA

We now want to examine which variables might load on which factors. To do so, we will perform EFA on a 2-factor model, and also on 1- and 3- factor models.

First, the 2-factor model:

```
athletic_efa2 <- fa(r = athletic_identity_matrix, nfactors = 2, cor = "poly")
fa.diagram(athletic_efa2, digits = 2, simple = TRUE)
```

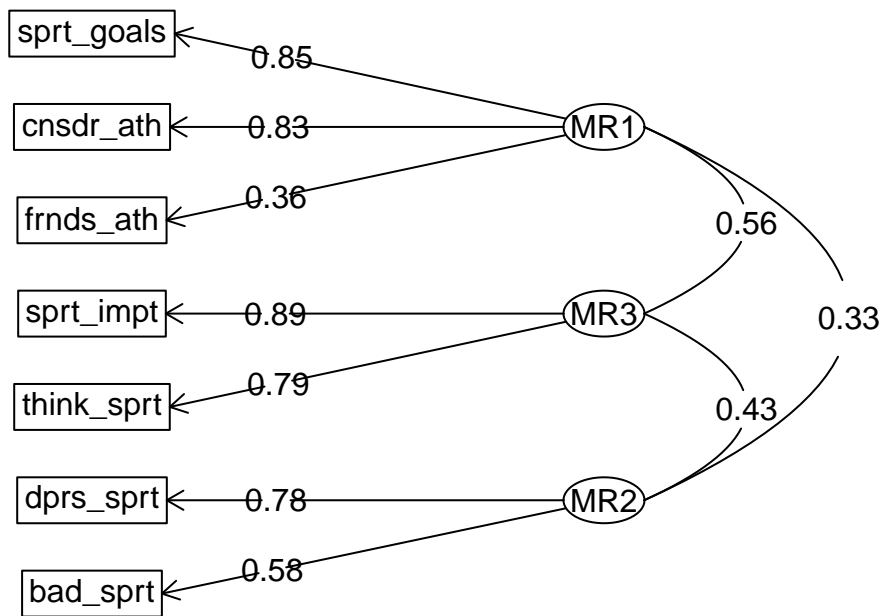
Factor Analysis



Now, the 3-factor model:

```
athletic_efa3 <- fa(r = athletic_identity_matrix, nfactors = 3, cor = "poly")
fa.diagram(athletic_efa3, digits = 2, simple = TRUE)
```

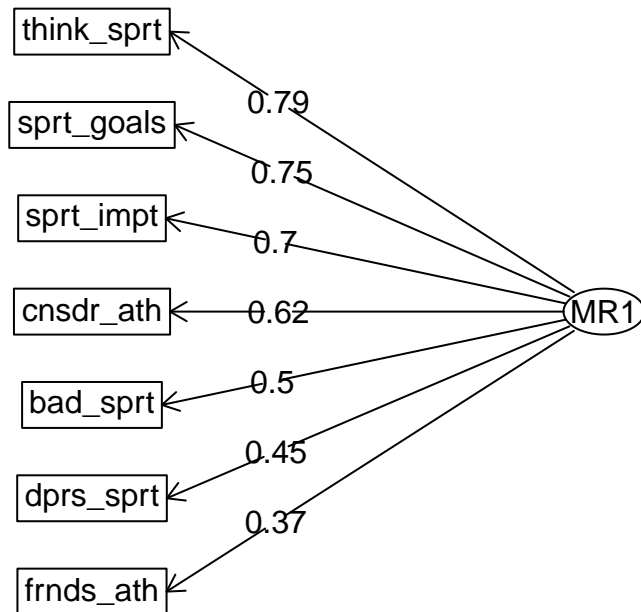
Factor Analysis



Now, the 1-factor model:

```
athletic_efa1 <- fa(r = athletic_identity_matrix, nfactors = 1, cor = "poly")
fa.diagram(athletic_efa1, digits = 2, simple = TRUE)
```

Factor Analysis



Reliability

LV 1: External Identity

```
external_identity <- c("cnsdr_ath", "sprt_goals", "frnds_ath")

external_identity_numeric <- athletes[,external_identity] %>% map_df(., as.numeric)

external_identity_matrix <- external_identity_numeric %>% as.matrix()
psych::alpha(external_identity_matrix)
```

```
##
## Reliability analysis
## Call: psych::alpha(x = external_identity_matrix)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
##     0.65     0.68    0.62    0.42 2.1 0.032  5.7 0.89     0.33
##
##   lower alpha upper      95% confidence boundaries
## 0.59 0.65 0.72
##
## Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r  S/N alpha se var.r med.r
## cnsdr_ath    0.47    0.49   0.33    0.33 0.97  0.052  NA  0.33
## sprt_goals    0.46    0.47   0.31    0.31 0.89  0.055  NA  0.31
## frnds_ath    0.75    0.76   0.61    0.61 3.15  0.025  NA  0.61
##
```

```
## Item statistics
##           n raw.r std.r r.cor r.drop mean  sd
## cnsdr_ath 356 0.79 0.82 0.71 0.53 5.9 1.11
## sprt_goals 356 0.78 0.83 0.72 0.56 6.1 0.96
## frnds_ath 356 0.76 0.70 0.41 0.35 5.2 1.38
##
## Non missing response frequency for each item
##           1 2 3 4 5 6 7 miss
## cnsdr_ath 0.01 0.01 0.03 0.05 0.24 0.33 0.35 0.02
## sprt_goals 0.00 0.00 0.02 0.03 0.20 0.35 0.40 0.02
## frnds_ath 0.01 0.04 0.06 0.10 0.31 0.29 0.17 0.02
```

Chronbach's alpha suggests we should drop frnds_ath.

```
external_identity <- c("cnsdr_ath", "sprt_goals")

external_identity_numeric <- athletes[,external_identity] %>% map_df(., as.numeric)

external_identity_matrix <- external_identity_numeric %>% as.matrix()
psych::alpha(external_identity_matrix)
```

```
##
## Reliability analysis
## Call: psych::alpha(x = external_identity_matrix)
##
##   raw_alpha std.alpha G6(smc) average_r S/N ase mean sd median_r
##     0.75     0.76     0.61     0.61 3.2 0.025 6 0.93 0.61
##
## lower alpha upper      95% confidence boundaries
## 0.7 0.75 0.8
##
## Reliability if an item is dropped:
##           raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## cnsdr_ath     0.71     0.61 0.37     0.61 1.6      NA 0 0.61
## sprt_goals     0.53     0.61 0.37     0.61 1.6      NA 0 0.61
##
## Item statistics
##           n raw.r std.r r.cor r.drop mean  sd
## cnsdr_ath 356 0.91 0.9 0.7 0.61 5.9 1.11
## sprt_goals 356 0.88 0.9 0.7 0.61 6.1 0.96
##
## Non missing response frequency for each item
##           1 2 3 4 5 6 7 miss
## cnsdr_ath 0.01 0.01 0.03 0.05 0.24 0.33 0.35 0.02
## sprt_goals 0.00 0.00 0.02 0.03 0.20 0.35 0.40 0.02
```

LV 2: Internal Value

```
internal_value <- c("sprt_impt", "think_sprt")

internal_value_numeric <- athletes[,internal_value] %>% map_df(., as.numeric)

internal_value_matrix <- internal_value_numeric %>% as.matrix()
psych::alpha(internal_value_matrix)
```

```
##
```

```
## Reliability analysis
## Call: psych::alpha(x = internal_value_matrix)
##
##      raw_alpha std.alpha G6(smc) average_r S/N ase mean sd median_r
##      0.81      0.81      0.67      0.67 4.1 0.02  5 1.4      0.67
##
## lower alpha upper      95% confidence boundaries
## 0.77 0.81 0.85
##
## Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## sprt_impt      0.67      0.67      0.45      0.67 2.1      NA      0 0.67
## think_sprt      0.68      0.67      0.45      0.67 2.1      NA      0 0.67
##
## Item statistics
##      n raw.r std.r r.cor r.drop mean sd
## sprt_impt 356 0.91 0.91 0.75 0.67 5.1 1.5
## think_sprt 356 0.92 0.91 0.75 0.67 4.9 1.5
##
## Non missing response frequency for each item
##      1 2 3 4 5 6 7 miss
## sprt_impt 0.03 0.04 0.10 0.10 0.28 0.27 0.18 0.02
## think_sprt 0.02 0.05 0.14 0.12 0.29 0.22 0.16 0.02
```

LV 3: Negative Events

```
negative_events <- c("dprs_sprt", "bad_sprt")

negative_events_numeric <- athletes[,negative_events] %>% map_df(., as.numeric)

negative_events_matrix <- negative_events_numeric %>% as.matrix()
psych::alpha(negative_events_matrix)
```

```
##
## Reliability analysis
## Call: psych::alpha(x = negative_events_matrix)
##
##      raw_alpha std.alpha G6(smc) average_r S/N ase mean sd median_r
##      0.63      0.63      0.46      0.46 1.7 0.039 5.6 1.2      0.46
##
## lower alpha upper      95% confidence boundaries
## 0.55 0.63 0.7
##
## Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## dprs_sprt      0.40      0.46      0.21      0.46 0.85      NA      0 0.46
## bad_sprt      0.53      0.46      0.21      0.46 0.85      NA      0 0.46
##
## Item statistics
##      n raw.r std.r r.cor r.drop mean sd
## dprs_sprt 356 0.83 0.85 0.58 0.46 5.7 1.3
## bad_sprt 356 0.88 0.85 0.58 0.46 5.5 1.4
##
## Non missing response frequency for each item
##      1 2 3 4 5 6 7 miss
```

```
## dprs_sprt 0.01 0.02 0.02 0.06 0.30 0.29 0.29 0.02
## bad_sprt 0.02 0.04 0.04 0.08 0.24 0.29 0.28 0.02
```

Our final model is as follows:

```
external_identity = sprt_goals + cnsdr_ath internal_value = sprt_impt + think_sprt negative_events =
dprs_sprt + bad_sprt
```

CFA

```
athlete_model <-
'external_identity =~ sprt_goals + cnsdr_ath
  internal_value =~ sprt_impt + think_sprt
  negative_events =~ dprs_sprt + bad_sprt'

athlete_2CFA = cfa(athlete_model, data = athletic_identity_matrix,
  ordered = names(athletic_identity_matrix),
  std.lv = TRUE)
summary(athlete_2CFA, fit.measures = TRUE)
```

```
## lavaan 0.6-10 ended normally after 27 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters      15
##
##                                     Used      Total
##      Number of observations          356        363
##
## Model Test User Model:
##
##      Test statistic                  5.234
##      Degrees of freedom                6
##      P-value (Chi-square)             0.514
##
## Model Test Baseline Model:
##
##      Test statistic                  617.425
##      Degrees of freedom              15
##      P-value                        0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      1.000
##      Tucker-Lewis Index (TLI)        1.003
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)    -3255.389
##      Loglikelihood unrestricted model (H1) -3252.772
##
##      Akaike (AIC)                    6540.778
##      Bayesian (BIC)                   6598.902
##      Sample-size adjusted Bayesian (BIC) 6551.316
##
```

```

## Root Mean Square Error of Approximation:
##
##   RMSEA                                0.000
##   90 Percent confidence interval - lower    0.000
##   90 Percent confidence interval - upper    0.064
##   P-value RMSEA <= 0.05                    0.872
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                0.017
##
## Parameter Estimates:
##
##   Standard errors                        Standard
##   Information                          Expected
##   Information saturated (h1) model      Structured
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)
##   external_identity =~
##     .sprt_goals      0.871    0.062   14.013    0.000
##     .cnsdr_ath       0.751    0.066   11.326    0.000
##   internal_value =~
##     .sprt_impt       1.076    0.083   12.962    0.000
##     .think_sprt      1.443    0.086   16.700    0.000
##   negative_events =~
##     .dprs_sprt       0.805    0.084    9.537    0.000
##     .bad_sprt        1.030    0.101   10.171    0.000
##
## Covariances:
##           Estimate  Std.Err  z-value  P(>|z|)
##   external_identity ~~
##     internal_value    0.511    0.054    9.498    0.000
##     negative_evnts    0.397    0.067    5.912    0.000
##   internal_value ~~
##     negative_evnts    0.513    0.061    8.432    0.000
##
## Variances:
##           Estimate  Std.Err  z-value  P(>|z|)
##   .sprt_goals        0.169    0.085    1.984    0.047
##   .cnsdr_ath         0.668    0.080    8.347    0.000
##   .sprt_impt         1.114    0.130    8.585    0.000
##   .think_sprt        0.251    0.180    1.394    0.163
##   .dprs_sprt         0.923    0.119    7.751    0.000
##   .bad_sprt          1.009    0.176    5.743    0.000
##   external_dntty     1.000
##   internal_value     1.000
##   negative_evnts     1.000

```