waveley_attempt

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How does an athlete's measure of athletic identity affect MHC-SF, as mediated through resilience?

Latent Variable Construction

Latent Variable 1: Athletic Identity

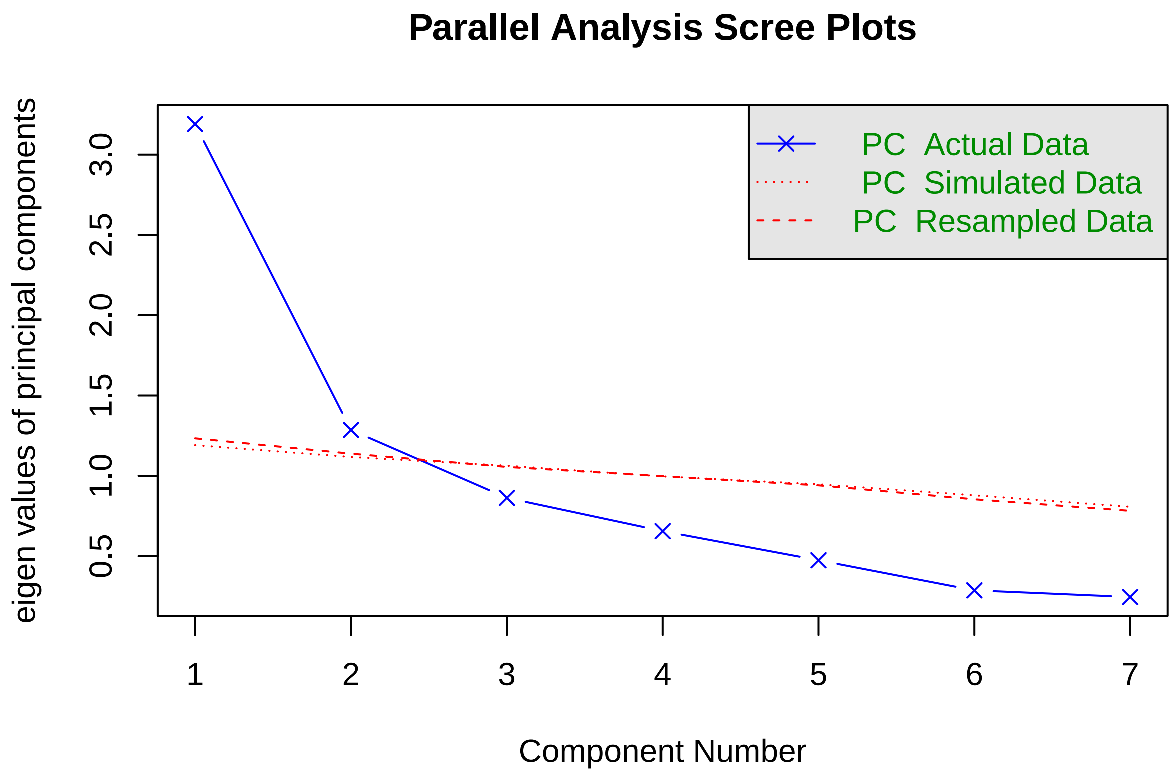
First, let's select the variables we are interested in.

```
athletic_identity <- c("cnsdr_ath", "sprt_goals", "frnds_ath", "sprt_impt", "think_sprt", "bad_sprt", "

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 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
```

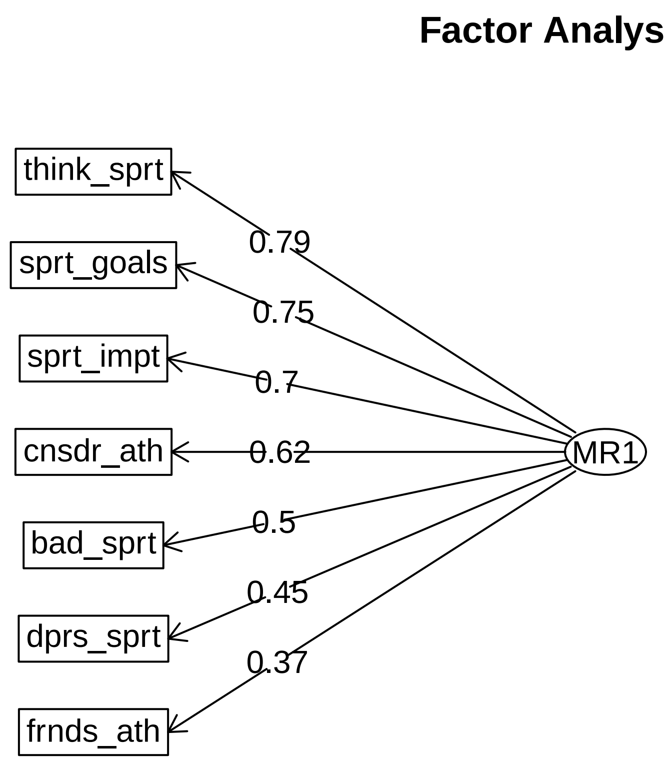
PCA indicates that two factors underlie these variables.

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.

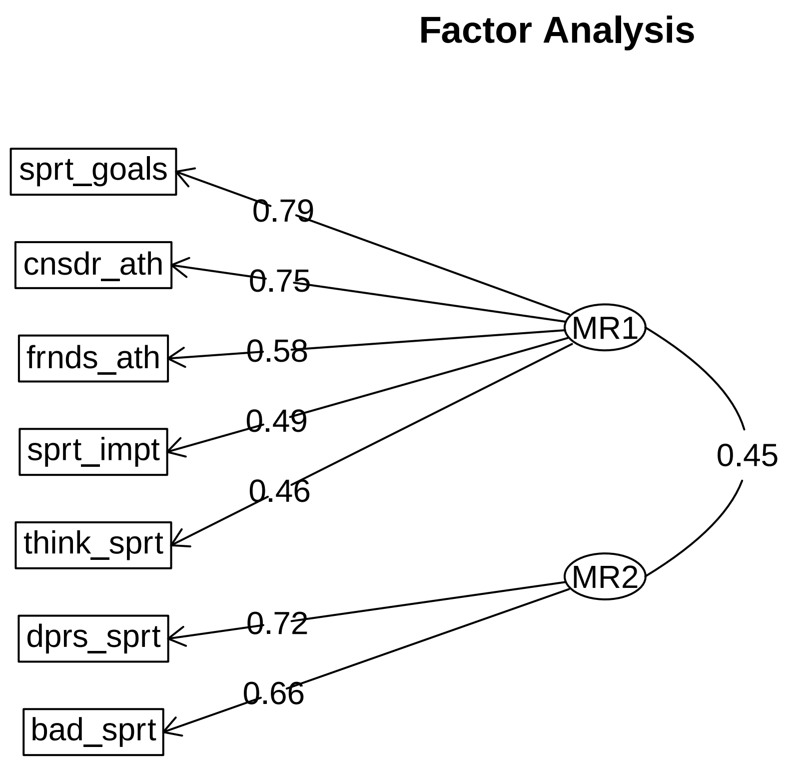
Now, the 1-factor model:

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



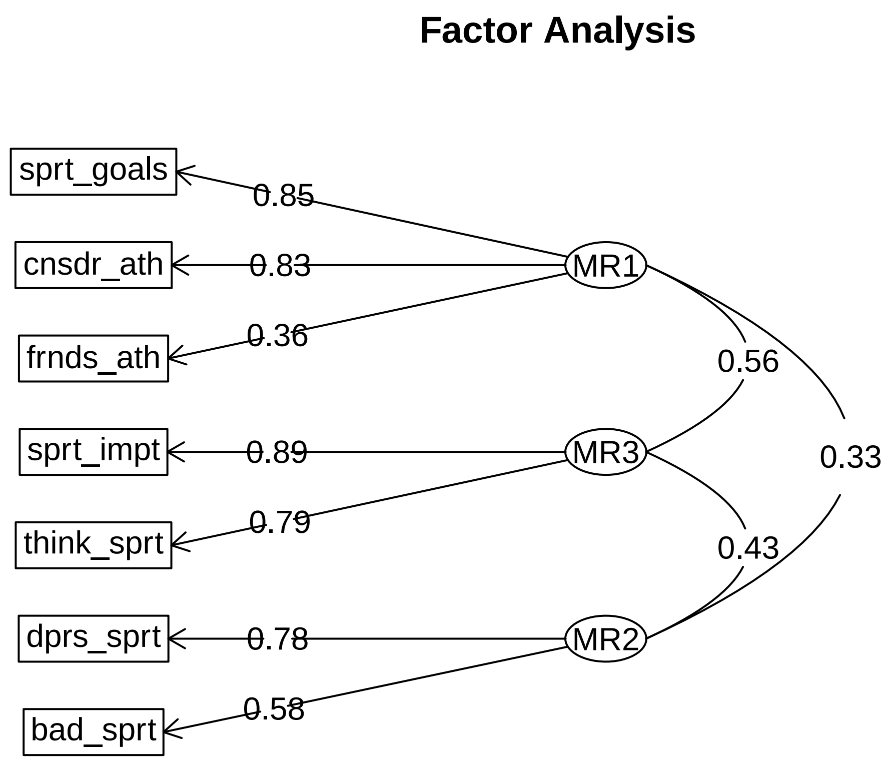
First, the 2-factor model:

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



Now, the 3-factor model:

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



The 3-factor model seems to fit the data the best, as it has the smallest BIC. We will proceed by using the 3-factor model for athletic_identity.

```
names <- c("1", "2", "3")
rmsea <- c(0.231, 0.234, 0.076)
bic <- c(201.72, 119.31, -8.36)
chi_sq <- c("2.3e-52", "7.1e-32", "0.025")

athletic_efa1 %>% summary()
```

```
##
## Factor analysis with Call: fa(r = athletic_identity_matrix, nfactors = 1, cor = "poly")
##
## Test of the hypothesis that 1 factor is sufficient.
## The degrees of freedom for the model is 14  and the objective function was  0.79
## The number of observations was  363  with Chi Square =  284.24  with prob <  2.3e-52
##
## The root mean square of the residuals (RMSA) is  0.12
## The df corrected root mean square of the residuals is  0.15
##
## Tucker Lewis Index of factoring reliability =  0.548
## RMSEA index =  0.231  and the 10 % confidence intervals are  0.208 0.255
## BIC =  201.72
```

```
athletic_efa2 %>% summary()
```

```
##
## Factor analysis with Call: fa(r = athletic_identity_matrix, nfactors = 2, cor = "poly")
```

```
##
## Test of the hypothesis that 2 factors are sufficient.
## The degrees of freedom for the model is 8  and the objective function was  0.47
## The number of observations was  363  with Chi Square =  166.46  with prob <  7.1e-32
##
## The root mean square of the residuals (RMSA) is  0.07
## The df corrected root mean square of the residuals is  0.12
##
## Tucker Lewis Index of factoring reliability =  0.535
## RMSEA index =  0.234  and the 10 % confidence intervals are  0.204 0.266
## BIC =  119.31
##  With factor correlations of
##      MR1  MR2
## MR1 1.00 0.45
## MR2 0.45 1.00
```

```r
athletic_efa3 %>% summary()
```

```
##
## Factor analysis with Call: fa(r = athletic_identity_matrix, nfactors = 3, cor = "poly")
##
## Test of the hypothesis that 3 factors are sufficient.
## The degrees of freedom for the model is 3  and the objective function was  0.03
## The number of observations was  363  with Chi Square =  9.33  with prob <  0.025
##
## The root mean square of the residuals (RMSA) is  0.01
## The df corrected root mean square of the residuals is  0.04
##
## Tucker Lewis Index of factoring reliability =  0.95
## RMSEA index =  0.076  and the 10 % confidence intervals are  0.024 0.134
## BIC =  -8.36
##  With factor correlations of
##      MR1  MR3  MR2
## MR1 1.00 0.56 0.33
## MR3 0.56 1.00 0.43
## MR2 0.33 0.43 1.00
```

```r
tibble(
  factor = names,
  rmsea = rmsea,
  bic = bic,
  chi_sq = chi_sq
) %>% knitr::kable(col.names = c("Number of Factors", "RMSEA", "BIC", "$\\chi^2$ p-value"))
```

Number of Factors	RMSEA	BIC	χ^2 p-value
1	0.231	201.72	2.3e-52
2	0.234	119.31	7.1e-32
3	0.076	-8.36	0.025

Reliability

We now want to assess the reliability of each of these constructs.

LV 1: External Identity

```r
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
```

Since the remove-one Chronbach's alpha indicates that reliability would improve quite a bit if `frnds_ath` is dropped, we will remove this variable from the latent variable structure for `external_identity`.

LV 2: Internal Value

```r
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 for athlete_identity is as follows:

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

CFA

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

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

```
## lavaan 0.6-10 ended normally after 39 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            0.677    0.073    9.247    0.000
##     cnsdr_ath             0.584    0.056   10.404    0.000
##   internal_value =~
##     sprt_impt             0.627    0.109    5.728    0.000
##     think_sprt            0.840    0.166    5.077    0.000
##   negative_events =~
##     dprs_sprt             0.625    0.078    8.053    0.000
##     bad_sprt              0.799    0.103    7.777    0.000
##   athlete_identity =~
##     external_dntty        0.809    0.143    5.658    0.000
##     internal_value        1.396    0.374    3.729    0.000
##     negative_evnts        0.813    0.152    5.364    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
##     athlete_idntty    1.000
##
## R-Square:
##                    Estimate
##     sprt_goals        0.818
##     cnsdr_ath         0.458
##     sprt_impt         0.509
##     think_sprt        0.893
##     dprs_sprt         0.413
##     bad_sprt          0.512
##     external_dntty    0.396
##     internal_value    0.661
##     negative_evnts    0.398
```

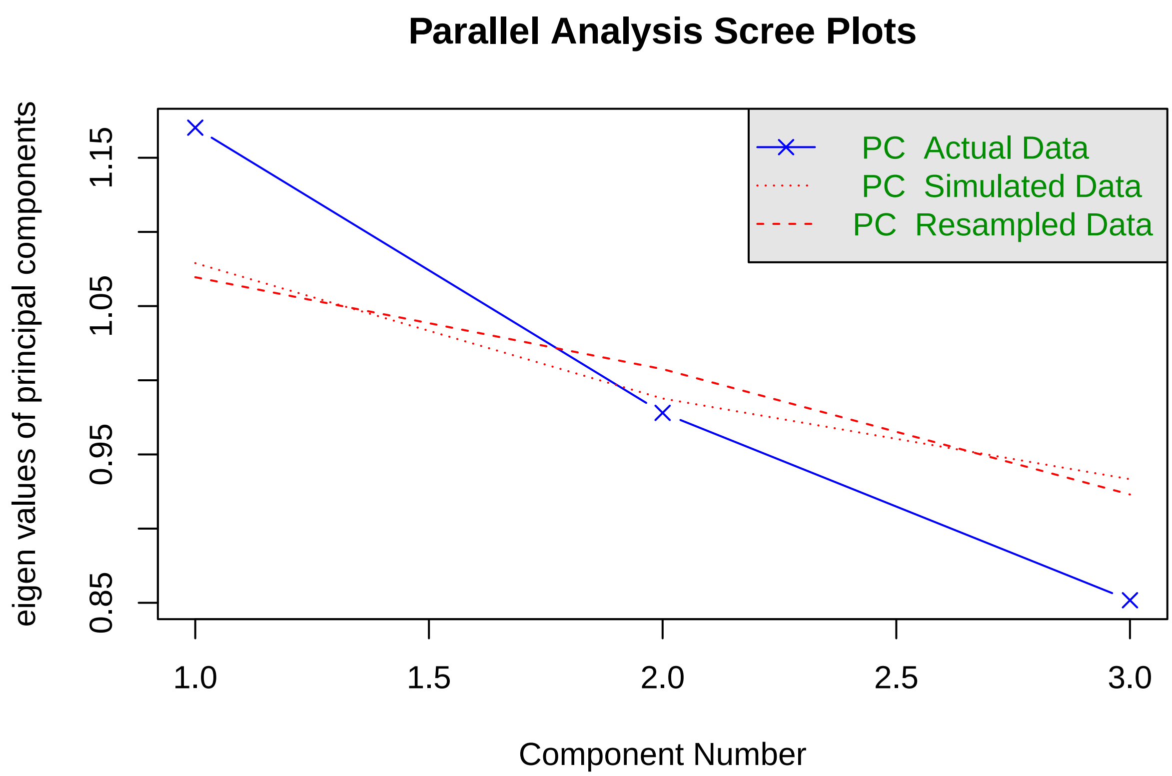
Latent Variable 2: Healthy Lifestyle

```
healthy_lifestyle <- c("hr_sleep", "smoking", "fruit_veg")

healthy_life_numeric <- athletes[,healthy_lifestyle] %>% map_df(., as.numeric)

healthy_life_matrix <- healthy_life_numeric %>% as.matrix()
```

Polychoric Correlations

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

```
health_parallel <- fa.parallel(healthy_life_matrix, fa = "pc")
```




```
## Parallel analysis suggests that the number of factors =  NA  and the number of components =  1
```

```
health_parallel$pc.values
```

```
## [1] 1.1702721 0.9780215 0.8517064
```

It appears that 1 component should underlie these three variables.

EFA

```
health_efa1 <- fa(r = healthy_life_matrix, nfactors = 1, cor = "poly")
fa.diagram(athletic_efa3, digits = 2, simple = TRUE)
```

Reliability

```
psych::alpha(healthy_life_matrix)
```

```
## Some items ( smoking ) were negatively correlated with the total scale and
## probably should be reversed.
## To do this, run the function again with the 'check.keys=TRUE' option
```

```
##
## Reliability analysis
## Call: psych::alpha(x = healthy_life_matrix)
##
##   raw_alpha std.alpha G6(smc) average_r   S/N  ase mean   sd median_r
##      -0.26     -0.21   -0.12    -0.061 -0.17 0.11  3.1 0.49    -0.07
##
##  lower alpha upper     95% confidence boundaries
## -0.47 -0.26 -0.04
##
##  Reliability if an item is dropped:
##           raw_alpha std.alpha G6(smc) average_r    S/N alpha se var.r  med.r
## hr_sleep     -0.112    -0.150  -0.070    -0.070 -0.130    0.089    NA -0.070
## smoking       0.043     0.055   0.028     0.028  0.058    0.078    NA  0.028
## fruit_veg    -0.330    -0.330  -0.142    -0.142 -0.248    0.140    NA -0.142
##
##  Item statistics
##             n raw.r std.r r.cor r.drop mean  sd
## hr_sleep  363  0.62  0.55   NaN -0.120 7.29 1.0
## smoking   363  0.61  0.49   NaN -0.156 1.56 1.1
## fruit_veg 363  0.31  0.59   NaN -0.033 0.55 0.5
```

Healthy lifestyle does not seem to be a reliable scale, so we will not use it in our model.

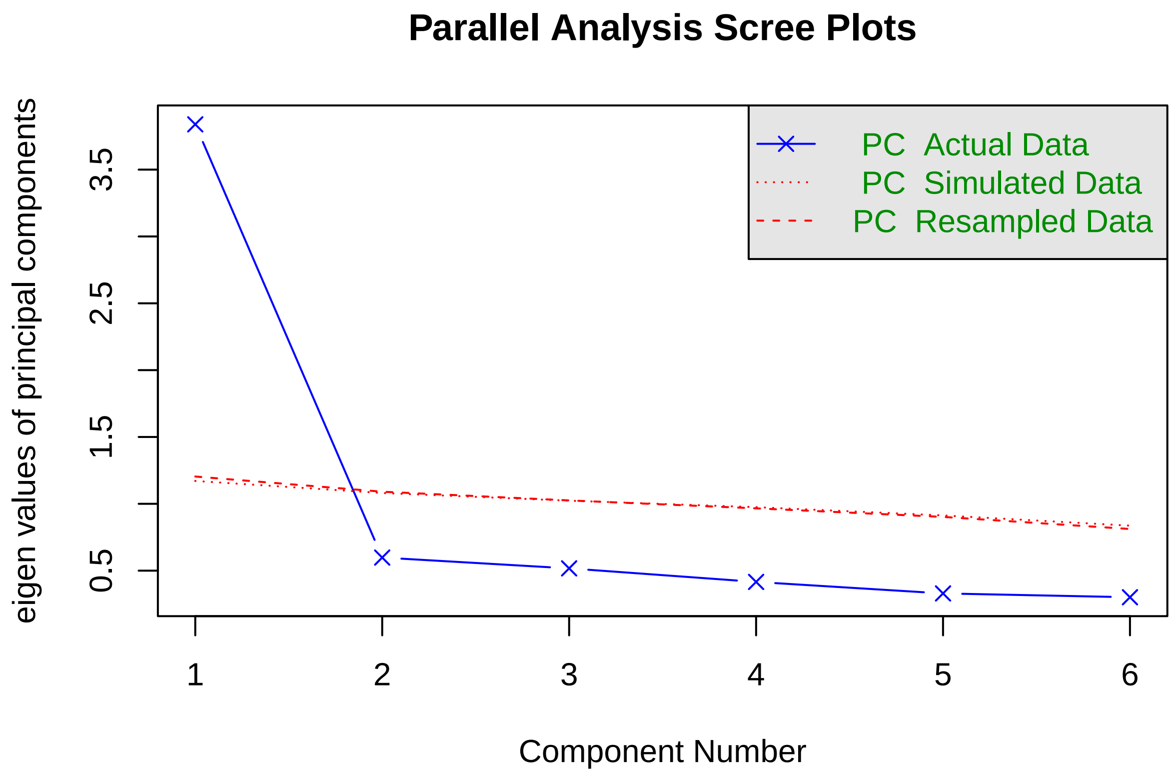
Latent Variable 3: Resilience

Finally, we will look at resilience.

```
resilience <- c("bounce", "strs_evnt", "strs_rcvr", "snap_back", "difficult", "setbacks")

resilience_numeric <- athletes[,resilience] %>% map_df(., as.numeric)

resilience_matrix <- resilience_numeric %>% as.matrix()
```

Polychoric Correlations

```
resilience_parallel <- fa.parallel(resilience_matrix, fa = "pc")
```




```
## Parallel analysis suggests that the number of factors =  NA  and the number of components =  1
```

```
resilience_parallel$pc.values
```

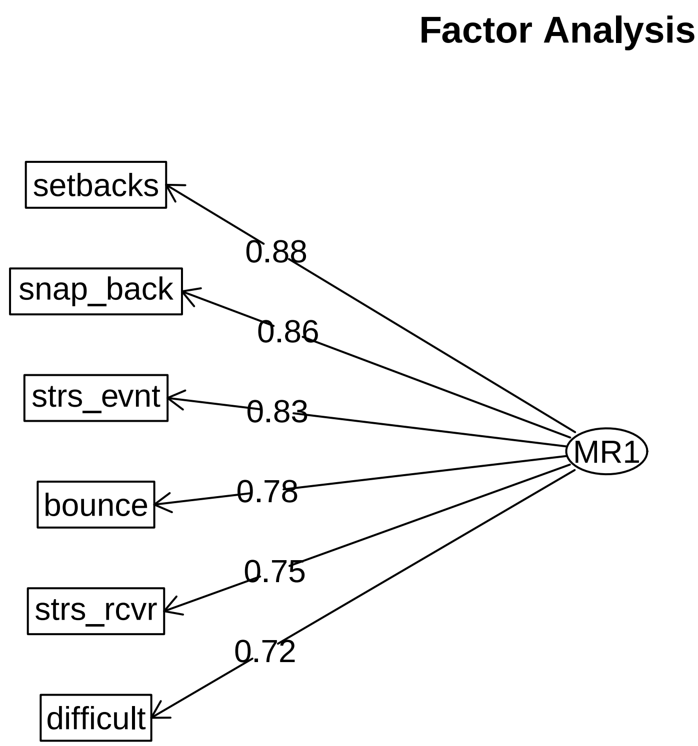
```
## [1] 3.8386245 0.5979661 0.5170194 0.4156602 0.3296245 0.3011053
```

It appears that a 1-factor model will sufficiently explain the variability across these variables.

EFA

First, we can do a 1-factor EFA model:

```
resilience_efa1 <- fa(r = resilience_matrix, nfactors = 1, cor = "poly")
fa.diagram(resilience_efa1, digits = 2, simple = TRUE)
```

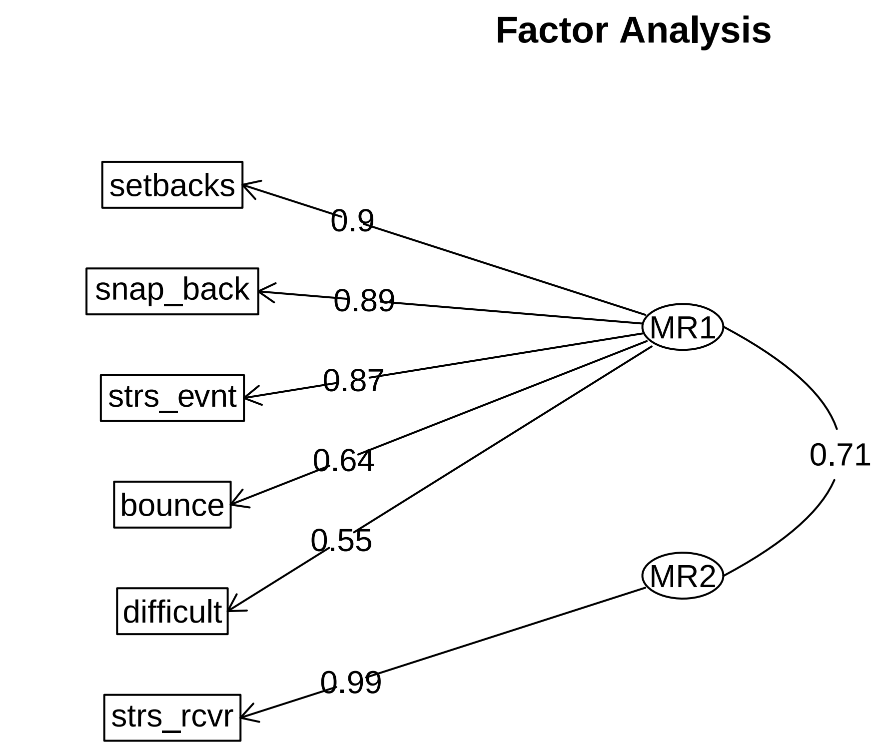



```
summary(resilience_efa1)
```

```
##
## Factor analysis with Call: fa(r = resilience_matrix, nfactors = 1, cor = "poly")
##
## Test of the hypothesis that 1 factor is sufficient.
## The degrees of freedom for the model is 9  and the objective function was  0.1
## The number of observations was  363  with Chi Square =  35.64  with prob <  4.6e-05
##
## The root mean square of the residuals (RMSA) is  0.03
## The df corrected root mean square of the residuals is  0.04
##
## Tucker Lewis Index of factoring reliability =  0.969
## RMSEA index =  0.09  and the 10 % confidence intervals are  0.06 0.123
## BIC =  -17.41
```

Now, we can try a 2-factor EFA model:

```
resilience_efa2 <- fa(r = resilience_matrix, nfactors = 2, cor = "poly")
fa.diagram(resilience_efa2, digits = 2, simple = TRUE)
```



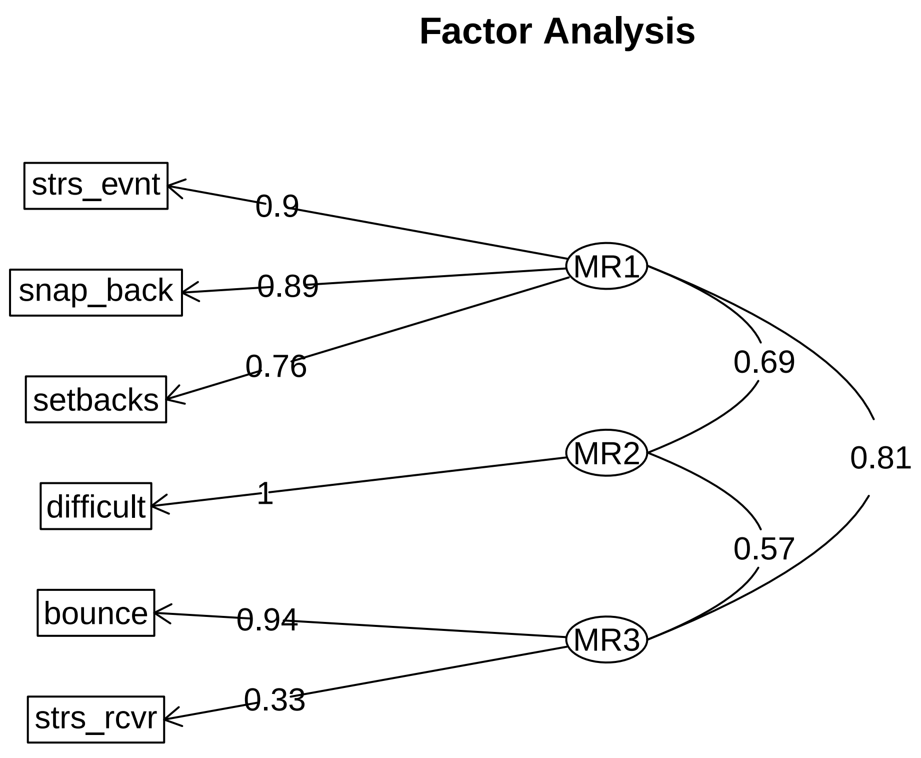

```
resilience_efa2
```

```
## Factor Analysis using method =  minres
## Call: fa(r = resilience_matrix, nfactors = 2, cor = "poly")
## Standardized loadings (pattern matrix) based upon correlation matrix
##            MR1   MR2   h2     u2 com
## bounce    0.64  0.18 0.60 0.4044 1.2
## strs_evnt 0.87 -0.04 0.71 0.2918 1.0
## strs_rcvr 0.01  0.99 1.00 0.0034 1.0
## snap_back 0.89 -0.02 0.76 0.2373 1.0
## difficult 0.55  0.20 0.50 0.5004 1.3
## setbacks  0.90 -0.02 0.79 0.2059 1.0
##
##                        MR1  MR2
## SS loadings           3.19 1.17
## Proportion Var        0.53 0.19
## Cumulative Var        0.53 0.73
## Proportion Explained  0.73 0.27
## Cumulative Proportion 0.73 1.00
##
##  With factor correlations of
##      MR1  MR2
## MR1 1.00 0.71
## MR2 0.71 1.00
##
## Mean item complexity =  1.1
```

```
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are  15  and the objective function was  3.98 with Chi Squa
## The degrees of freedom for the model are 4  and the objective function was  0.02
##
## The root mean square of the residuals (RMSR) is  0.01
## The df corrected root mean square of the residuals is  0.02
##
## The harmonic number of observations is  322 with the empirical chi square  1.5  with prob <  0.83
## The total number of observations was  363  with Likelihood Chi Square =  8.56  with prob <  0.073
##
## Tucker Lewis Index of factoring reliability =  0.988
## RMSEA index =  0.056  and the 90 % confidence intervals are  0 0.109
## BIC =  -15.02
## Fit based upon off diagonal values = 1
## Measures of factor score adequacy
##                                                    MR1  MR2
## Correlation of (regression) scores with factors   0.96 1.00
## Multiple R square of scores with factors          0.93 1.00
## Minimum correlation of possible factor scores     0.85 0.99
```

Finally, we can try a 3-factor EFA model:

```r
resilience_efa3 <- fa(r = resilience_matrix, nfactors = 3, cor = "poly")
fa.diagram(resilience_efa3, digits = 2, simple = TRUE)
```



```r
summary(resilience_efa3)
```

```
##
## Factor analysis with Call: fa(r = resilience_matrix, nfactors = 3, cor = "poly")
##
## Test of the hypothesis that 3 factors are sufficient.
## The degrees of freedom for the model is 0  and the objective function was  0
## The number of observations was  363  with Chi Square =  0.18  with prob <  NA
##
## The root mean square of the residuals (RMSA) is  0
## The df corrected root mean square of the residuals is  NA
##
## Tucker Lewis Index of factoring reliability =  -Inf
##  With factor correlations of
##      MR1  MR2  MR3
## MR1 1.00 0.69 0.81
## MR2 0.69 1.00 0.57
## MR3 0.81 0.57 1.00
```

```r
names <- c("1", "2")
rmsea <- c(0.09, 0.056)
bic <- c(-17.41, -15.02)
chi_sq <- c("4.6e-05", "0.073")

athletic_efa1 %>% summary()
```

```
##
## Factor analysis with Call: fa(r = athletic_identity_matrix, nfactors = 1, cor = "poly")
##
## Test of the hypothesis that 1 factor is sufficient.
## The degrees of freedom for the model is 14  and the objective function was  0.79
## The number of observations was  363  with Chi Square =  284.24  with prob <  2.3e-52
##
## The root mean square of the residuals (RMSA) is  0.12
## The df corrected root mean square of the residuals is  0.15
##
## Tucker Lewis Index of factoring reliability =  0.548
## RMSEA index =  0.231  and the 10 % confidence intervals are  0.208 0.255
## BIC =  201.72
```

```r
athletic_efa2 %>% summary()
```

```
##
## Factor analysis with Call: fa(r = athletic_identity_matrix, nfactors = 2, cor = "poly")
##
## Test of the hypothesis that 2 factors are sufficient.
## The degrees of freedom for the model is 8  and the objective function was  0.47
## The number of observations was  363  with Chi Square =  166.46  with prob <  7.1e-32
##
## The root mean square of the residuals (RMSA) is  0.07
## The df corrected root mean square of the residuals is  0.12
##
## Tucker Lewis Index of factoring reliability =  0.535
## RMSEA index =  0.234  and the 10 % confidence intervals are  0.204 0.266
## BIC =  119.31
```

```
##  With factor correlations of
##      MR1  MR2
## MR1 1.00 0.45
## MR2 0.45 1.00
```

```
athletic_efa3 %>% summary()
```

```
##
## Factor analysis with Call: fa(r = athletic_identity_matrix, nfactors = 3, cor = "poly")
##
## Test of the hypothesis that 3 factors are sufficient.
## The degrees of freedom for the model is 3  and the objective function was  0.03
## The number of observations was  363  with Chi Square =  9.33  with prob <  0.025
##
## The root mean square of the residuals (RMSA) is  0.01
## The df corrected root mean square of the residuals is  0.04
##
## Tucker Lewis Index of factoring reliability =  0.95
## RMSEA index =  0.076  and the 10 % confidence intervals are  0.024 0.134
## BIC =  -8.36
##  With factor correlations of
##      MR1  MR3  MR2
## MR1 1.00 0.56 0.33
## MR3 0.56 1.00 0.43
## MR2 0.33 0.43 1.00
```

```
tibble(
  factor = names,
  rmsea = rmsea,
  bic = bic,
  chi_sq = chi_sq
) %>% knitr::kable(col.names = c("Number of Factors", "RMSEA", "BIC", "$\\chi^2$ p-value"))
```

Number of Factors	RMSEA	BIC	χ^2 p-value
1	0.090	-17.41	4.6e-05
2	0.056	-15.02	0.073

Reliability

```
psych::alpha(resilience_matrix)
```

```
##
## Reliability analysis
## Call: psych::alpha(x = resilience_matrix)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean   sd median_r
##       0.89      0.89    0.87      0.57 7.8 0.0092  3.6 0.79     0.55
##
##  lower alpha upper     95% confidence boundaries
## 0.87 0.89 0.9
##
##  Reliability if an item is dropped:
##          raw_alpha std.alpha G6(smc) average_r S/N alpha se  var.r med.r
## bounce        0.87      0.87    0.85      0.57 6.7   0.0109 0.0054  0.54
```

```
## strs_evnt      0.86      0.86    0.84      0.56 6.3   0.0115 0.0043  0.55
## strs_rcvr      0.87      0.87    0.85      0.58 6.9   0.0104 0.0066  0.58
## snap_back      0.86      0.86    0.84      0.55 6.1   0.0117 0.0036  0.55
## difficult      0.88      0.88    0.86      0.59 7.3   0.0099 0.0038  0.58
## setbacks       0.85      0.85    0.83      0.54 5.9   0.0121 0.0036  0.53
##
##  Item statistics
##             n raw.r std.r r.cor r.drop mean   sd
## bounce    322  0.78  0.79  0.73   0.69  4.0 0.90
## strs_evnt 322  0.83  0.82  0.78   0.73  3.4 1.08
## strs_rcvr 322  0.77  0.77  0.70   0.66  3.6 0.99
## snap_back 322  0.83  0.83  0.79   0.74  3.5 1.01
## difficult 322  0.74  0.74  0.66   0.62  3.4 0.99
## setbacks  322  0.85  0.85  0.83   0.78  3.6 0.99
##
## Non missing response frequency for each item
##              1    2    3    4    5 miss
## bounce    0.02 0.06 0.15 0.49 0.28 0.11
## strs_evnt 0.05 0.18 0.29 0.34 0.14 0.11
## strs_rcvr 0.02 0.14 0.25 0.42 0.16 0.11
## snap_back 0.02 0.18 0.19 0.48 0.13 0.11
## difficult 0.02 0.19 0.28 0.39 0.11 0.11
## setbacks  0.03 0.13 0.23 0.47 0.15 0.11
```

Chronbach's alpha is 0.89 (0.88, 0.91). No items can be dropped to improve this measure, so we will keep all of them in this latent variable.

CFA

```
resilience_model <-
' resilience =~ bounce + strs_evnt + strs_rcvr + snap_back + difficult + setbacks
'

resilience_cfa = cfa(resilience_model, data = resilience_matrix,
                   ordered = names(resilience_matrix),
                   std.lv = TRUE)
summary(resilience_cfa, fit.measures = TRUE, rsquare = TRUE)
```

```
## lavaan 0.6-10 ended normally after 17 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        12
##
##                                                   Used       Total
##   Number of observations                           322         363
##
## Model Test User Model:
##
##   Test statistic                                20.216
##   Degrees of freedom                                 9
##   P-value (Chi-square)                           0.017
##
## Model Test Baseline Model:
##
```

```
##   Test statistic                               971.399
##   Degrees of freedom                                15
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.988
##   Tucker-Lewis Index (TLI)                       0.980
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -2247.133
##   Loglikelihood unrestricted model (H1)      -2237.025
##
##   Akaike (AIC)                                4518.266
##   Bayesian (BIC)                              4563.561
##   Sample-size adjusted Bayesian (BIC)         4525.499
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.062
##   90 Percent confidence interval - lower         0.025
##   90 Percent confidence interval - upper         0.099
##   P-value RMSEA <= 0.05                          0.253
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.026
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   resilience =~
##     bounce            0.662    0.045   14.732    0.000
##     strs_evnt         0.852    0.052   16.419    0.000
##     strs_rcvr         0.679    0.051   13.415    0.000
##     snap_back         0.814    0.048   17.031    0.000
##     difficult         0.644    0.051   12.559    0.000
##     setbacks          0.828    0.046   17.954    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .bounce            0.376    0.034   10.974    0.000
##    .strs_evnt         0.433    0.042   10.201    0.000
##    .strs_rcvr         0.524    0.046   11.396    0.000
##    .snap_back         0.345    0.035    9.824    0.000
##    .difficult         0.565    0.049   11.614    0.000
##    .setbacks          0.286    0.031    9.119    0.000
##     resilience        1.000
```

```
##
## R-Square:
##                    Estimate
##     bounce            0.538
##     strs_evnt         0.626
##     strs_rcvr         0.468
##     snap_back         0.658
##     difficult         0.423
##     setbacks          0.706
```

Final CFA

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

 athlete_identity =~ external_identity + internal_value + negative_events

 resilience =~ bounce + strs_evnt + strs_rcvr + snap_back + difficult + setbacks
'
fin_df <- athletes %>% map_df(., as.numeric)

final_cfa = cfa(final_model,
                data = fin_df,
                std.lv = TRUE)
summary(final_cfa, fit.measures = TRUE, rsquare=TRUE)
```

```
## lavaan 0.6-10 ended normally after 42 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        30
##
##                                                   Used       Total
##   Number of observations                           322         363
##
## Model Test User Model:
##
##   Test statistic                               106.384
##   Degrees of freedom                                61
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                              1645.418
##   Degrees of freedom                                78
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.971
##   Tucker-Lewis Index (TLI)                       0.963
```

```
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -5730.730
##   Loglikelihood unrestricted model (H1)     -5677.538
##
##   Akaike (AIC)                              11521.460
##   Bayesian (BIC)                            11634.696
##   Sample-size adjusted Bayesian (BIC)       11539.540
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                         0.048
##   90 Percent confidence interval - lower        0.032
##   90 Percent confidence interval - upper        0.063
##   P-value RMSEA <= 0.05                         0.564
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                          0.060
##
## 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            0.623    0.064    9.726    0.000
##     cnsdr_ath             0.605    0.062    9.806    0.000
##     frnds_ath             0.407    0.067    6.101    0.000
##   internal_value =~
##     sprt_impt             0.574    0.123    4.666    0.000
##     think_sprt            0.767    0.183    4.187    0.000
##   negative_events =~
##     dprs_sprt             0.634    0.082    7.694    0.000
##     bad_sprt              0.805    0.108    7.445    0.000
##   athlete_identity =~
##     external_dntty        0.866    0.156    5.539    0.000
##     internal_value        1.540    0.478    3.223    0.001
##     negative_evnts        0.777    0.150    5.178    0.000
##   resilience =~
##     bounce                0.661    0.045   14.692    0.000
##     strs_evnt             0.853    0.052   16.460    0.000
##     strs_rcvr             0.678    0.051   13.378    0.000
##     snap_back             0.814    0.048   17.025    0.000
##     difficult             0.644    0.051   12.557    0.000
##     setbacks              0.829    0.046   17.995    0.000
##
## Covariances:
##                      Estimate  Std.Err  z-value  P(>|z|)
##   athlete_identity ~~
```

```
##     resilience          -0.142    0.069   -2.066    0.039
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .sprt_goals        0.229    0.062    3.708    0.000
##    .cnsdr_ath         0.618    0.075    8.264    0.000
##    .frnds_ath         1.575    0.130   12.135    0.000
##    .sprt_impt         1.173    0.137    8.573    0.000
##    .think_sprt        0.288    0.181    1.588    0.112
##    .dprs_sprt         0.959    0.129    7.421    0.000
##    .bad_sprt          1.017    0.187    5.435    0.000
##    .bounce            0.378    0.034   10.995    0.000
##    .strs_evnt         0.431    0.042   10.187    0.000
##    .strs_rcvr         0.526    0.046   11.411    0.000
##    .snap_back         0.345    0.035    9.839    0.000
##    .difficult         0.565    0.049   11.619    0.000
##    .setbacks          0.284    0.031    9.098    0.000
##    .external_dntty    1.000
##    .internal_value    1.000
##    .negative_evnts    1.000
##     athlete_idntty    1.000
##     resilience        1.000
##
## R-Square:
##                    Estimate
##     sprt_goals        0.748
##     cnsdr_ath         0.509
##     frnds_ath         0.156
##     sprt_impt         0.487
##     think_sprt        0.873
##     dprs_sprt         0.402
##     bad_sprt          0.506
##     bounce            0.536
##     strs_evnt         0.628
##     strs_rcvr         0.466
##     snap_back         0.658
##     difficult         0.423
##     setbacks          0.707
##     external_dntty    0.429
##     internal_value    0.703
##     negative_evnts    0.376
```

Modification Indices

```
modindices(final_cfa, power = TRUE, sort = TRUE, minimum.value = 10)
```

```
##                   lhs op              rhs     mi    epc sepc.all delta   ncp
## 169 external_identity ~~       resilience 10.801  0.263    0.263   0.1 1.562
## 170    internal_value ~~  negative_events 10.801 -2.559   -2.559   0.1 0.016
## 168 external_identity ~~ athlete_identity 10.801  1.853    1.853   0.1 0.031
##     power decision
## 169 0.239  **(m)**
## 170 0.052  **(m)**
## 168 0.054  **(m)**
```

Structural Equation Modeling

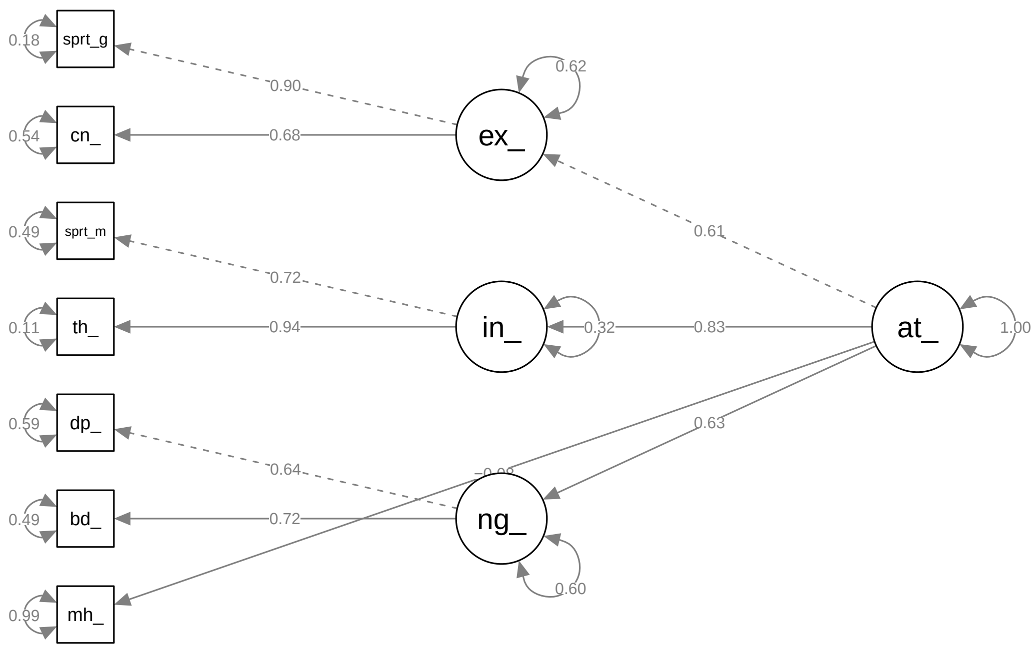
Let's first start with a basic SEM, relating athletic identity to MHC-SF.

```
basic_athlete_sem <- '
  # measurement model
    external_identity =~ sprt_goals + cnsdr_ath
    internal_value =~ sprt_impt + think_sprt
    negative_events =~ dprs_sprt + bad_sprt

    athlete_identity =~ external_identity + internal_value + negative_events

  # structural model - direct effects
    mhc_sf ~ a*athlete_identity
'

basic_athlete_sem_fit <- sem(basic_athlete_sem,
                       data = athletes,
                       sample.cov = TRUE,
                       missing = "ML")

summary(basic_athlete_sem_fit, standardized=TRUE)
```

```
## lavaan 0.6-10 ended normally after 68 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        24
##
##                                                   Used       Total
##   Number of observations                           356         363
##   Number of missing patterns                         2
##
## Model Test User Model:
##
##   Test statistic                                32.741
##   Degrees of freedom                                11
##   P-value (Chi-square)                           0.001
##
## 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
##   external_identity =~
##     sprt_goals              1.000                               0.872    0.905
##     cnsdr_ath               0.861    0.109    7.896    0.000    0.751    0.676
##   internal_value =~
##     sprt_impt               1.000                               1.078    0.715
##     think_sprt              1.337    0.135    9.912    0.000    1.441    0.943
##   negative_events =~
##     dprs_sprt               1.000                               0.803    0.641
```

```
##     bad_sprt              1.286    0.203    6.322    0.000    1.032    0.718
##   athlete_identity =~
##     external_dntty        1.000                               0.613    0.613
##     internal_value        1.667    0.326    5.120    0.000    0.827    0.827
##     negative_evnts        0.951    0.171    5.555    0.000    0.633    0.633
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   mhc_sf ~
##     athlt_dntt (a)   -1.982    1.657   -1.196    0.232   -1.060   -0.083
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        5.067    0.051   99.250    0.000    5.067    5.260
##    .cnsdr_ath         5.876    0.059   99.896    0.000    5.876    5.294
##    .sprt_impt         5.110    0.080   63.963    0.000    5.110    3.390
##    .think_sprt        4.904    0.081   60.577    0.000    4.904    3.211
##    .dprs_sprt         5.666    0.066   85.293    0.000    5.666    4.521
##    .bad_sprt          5.506    0.076   72.198    0.000    5.506    3.826
##    .mhc_sf           32.125    0.703   45.668    0.000   32.125    2.502
##    .external_dntty    0.000                               0.000    0.000
##    .internal_value    0.000                               0.000    0.000
##    .negative_evnts    0.000                               0.000    0.000
##     athlete_idntty    0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        0.168    0.087    1.932    0.053    0.168    0.181
##    .cnsdr_ath         0.668    0.081    8.240    0.000    0.668    0.543
##    .sprt_impt         1.110    0.130    8.511    0.000    1.110    0.489
##    .think_sprt        0.258    0.180    1.432    0.152    0.258    0.111
##    .dprs_sprt         0.926    0.118    7.819    0.000    0.926    0.589
##    .bad_sprt          1.004    0.176    5.720    0.000    1.004    0.485
##    .mhc_sf          163.698   12.728   12.861    0.000  163.698    0.993
##    .external_dntty    0.474    0.099    4.773    0.000    0.624    0.624
##    .internal_value    0.367    0.143    2.567    0.010    0.316    0.316
##    .negative_evnts    0.387    0.097    3.986    0.000    0.599    0.599
##     athlete_idntty    0.286    0.069    4.143    0.000    1.000    1.000
```

```r
# graph looks cleaner
semPaths(basic_athlete_sem_fit,
         what = "paths",
         whatLabels = "std",
         reorder = FALSE,
         layout = "tree3",
         rotation = 4,
         intercepts = FALSE)
```



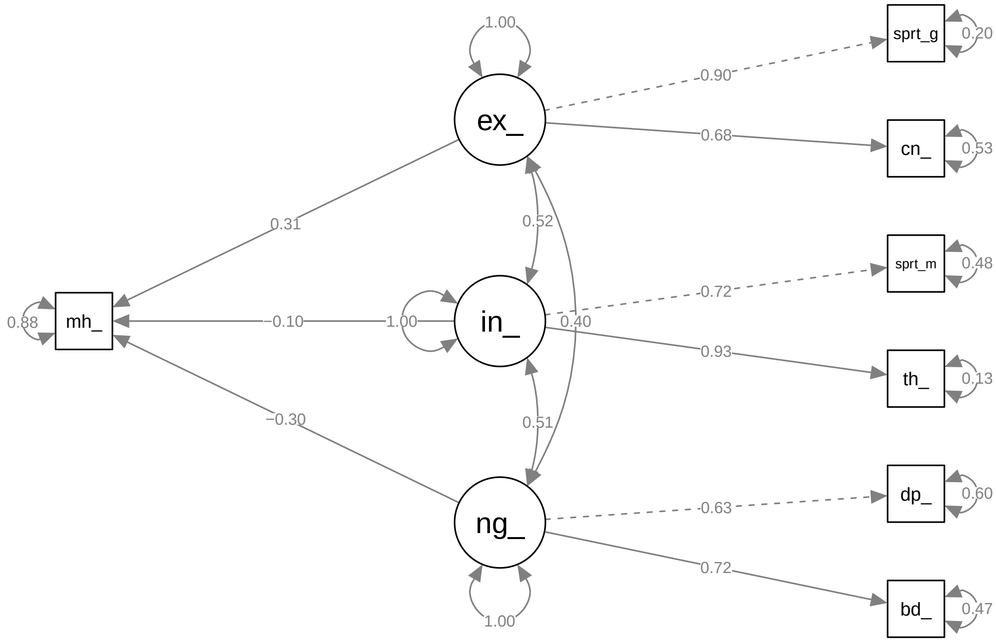

```
basic_athlete_sem <- '
  # measurement model
    external_identity =~ sprt_goals + cnsdr_ath
    internal_value =~ sprt_impt + think_sprt
    negative_events =~ dprs_sprt + bad_sprt

  # structural model - direct effects
    mhc_sf ~ a*external_identity + b*internal_value + c*negative_events
'

basic_athlete_sem_fit <- sem(basic_athlete_sem,
                        data = athletes,
                        sample.cov = TRUE,
                        missing = "ML")

summary(basic_athlete_sem_fit, standardized=TRUE)
```

```
## lavaan 0.6-10 ended normally after 79 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        26
##
##                                                   Used       Total
##   Number of observations                           356         363
##   Number of missing patterns                         2
```

```
##
## Model Test User Model:
##
##   Test statistic                                 7.984
##   Degrees of freedom                                 9
##   P-value (Chi-square)                           0.536
##
## 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
##   external_identity =~
##     sprt_goals              1.000                                0.864    0.897
##     cnsdr_ath               0.877    0.101    8.718    0.000    0.758    0.683
##   internal_value =~
##     sprt_impt               1.000                                1.089    0.723
##     think_sprt              1.309    0.130   10.057    0.000    1.426    0.933
##   negative_events =~
##     dprs_sprt               1.000                                0.795    0.634
##     bad_sprt                1.311    0.195    6.736    0.000    1.043    0.725
##
## Regressions:
##                      Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   mhc_sf ~
##     extrnl_dnt (a)    4.594    1.245    3.691    0.000    3.968    0.309
##     internl_vl (b)   -1.227    0.992   -1.237    0.216   -1.336   -0.104
##     negtv_vnts (c)   -4.847    1.477   -3.281    0.001   -3.854   -0.300
##
## Covariances:
##                          Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   external_identity ~~
##     internal_value          0.489    0.078    6.287    0.000    0.520    0.520
##     negative_evnts          0.273    0.059    4.600    0.000    0.397    0.397
##   internal_value ~~
##     negative_evnts          0.445    0.085    5.252    0.000    0.514    0.514
##
## Intercepts:
##                      Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        5.067    0.051   99.250    0.000    5.067    5.260
##    .cnsdr_ath         5.876    0.059   99.896    0.000    5.876    5.294
##    .sprt_impt         5.110    0.080   63.963    0.000    5.110    3.390
##    .think_sprt        4.904    0.081   60.577    0.000    4.904    3.211
##    .dprs_sprt         5.666    0.066   85.293    0.000    5.666    4.521
##    .bad_sprt          5.506    0.076   72.198    0.000    5.506    3.826
##    .mhc_sf           32.128    0.703   45.726    0.000   32.128    2.500
##     external_dntty    0.000                               0.000    0.000
##     internal_value    0.000                               0.000    0.000
##     negative_evnts    0.000                               0.000    0.000
##
## Variances:
```

```
##                      Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals          0.182    0.076    2.395    0.017    0.182    0.196
##    .cnsdr_ath           0.658    0.076    8.684    0.000    0.658    0.534
##    .sprt_impt           1.086    0.130    8.359    0.000    1.086    0.478
##    .think_sprt          0.301    0.175    1.723    0.085    0.301    0.129
##    .dprs_sprt           0.939    0.112    8.366    0.000    0.939    0.597
##    .bad_sprt            0.983    0.167    5.874    0.000    0.983    0.475
##    .mhc_sf            145.169   12.250   11.851    0.000  145.169    0.879
##     external_dntty      0.746    0.101    7.373    0.000    1.000    1.000
##     internal_value      1.186    0.181    6.568    0.000    1.000    1.000
##     negative_evnts      0.632    0.129    4.915    0.000    1.000    1.000
```

```r
# graph looks cleaner
semPaths(basic_athlete_sem_fit,
         what = "paths",
         whatLabels = "std",
         reorder = FALSE,
         layout = "tree3",
         rotation = 4,
         intercepts = FALSE)
```




```r
basic_athlete_sem <- '
  # measurement model
    external_identity =~ sprt_goals + cnsdr_ath
    internal_value =~ sprt_impt + think_sprt
    negative_events =~ dprs_sprt + bad_sprt

```

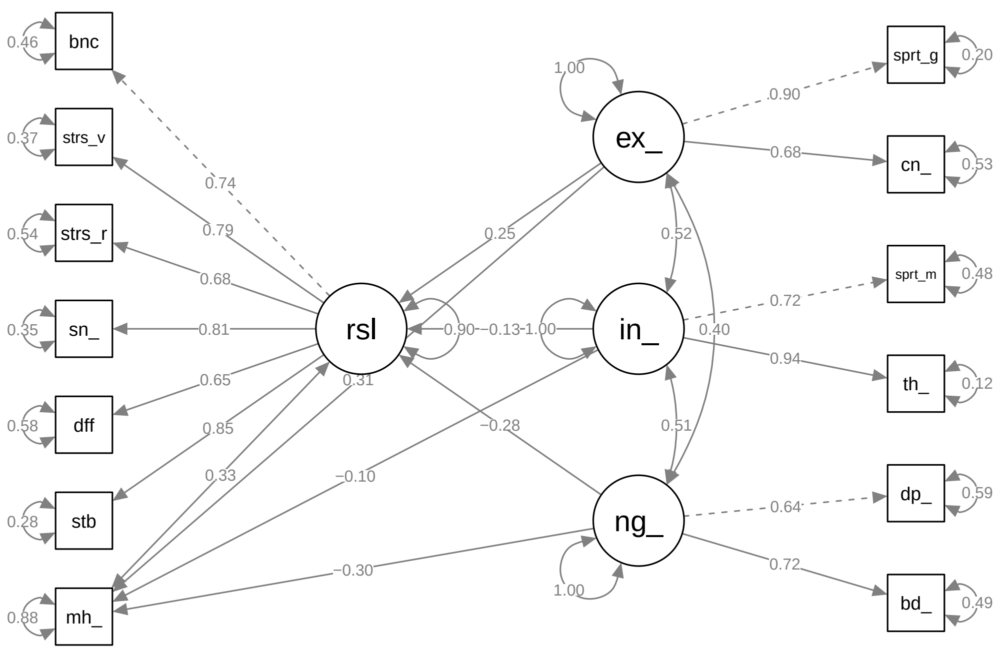
```
    resilience =~ bounce + strs_evnt + strs_rcvr + snap_back + difficult + setbacks

  # structural model - direct effects
    mhc_sf ~ a*external_identity + b*internal_value + c*negative_events
    resilience ~ d*external_identity
    resilience ~ e*internal_value
    resilience ~ f*negative_events
'

basic_athlete_sem_fit <- sem(basic_athlete_sem,
                       data = athletes,
                       sample.cov = TRUE,
                       missing = "ML")

summary(basic_athlete_sem_fit, standardized=TRUE)
```

```
## lavaan 0.6-10 ended normally after 103 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        48
##
##                                                   Used       Total
##   Number of observations                           356         363
##   Number of missing patterns                         3
##
## Model Test User Model:
##
##   Test statistic                                71.986
##   Degrees of freedom                                56
##   P-value (Chi-square)                           0.074
##
## 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
##   external_identity =~
##     sprt_goals              1.000                                0.863    0.896
##     cnsdr_ath               0.878    0.100    8.815    0.000    0.758    0.683
##   internal_value =~
##     sprt_impt               1.000                                1.083    0.719
##     think_sprt              1.323    0.132   10.044    0.000    1.433    0.938
##   negative_events =~
##     dprs_sprt               1.000                                0.804    0.641
##     bad_sprt                1.283    0.186    6.914    0.000    1.031    0.717
##   resilience =~
##     bounce                  1.000                                0.665    0.735
##     strs_evnt               1.287    0.094   13.747    0.000    0.855    0.793
##     strs_rcvr               1.015    0.085   11.891    0.000    0.675    0.679
##     snap_back               1.224    0.087   14.113    0.000    0.814    0.809
```

```
##     difficult             0.969    0.086   11.213    0.000    0.644    0.650
##     setbacks              1.256    0.085   14.742    0.000    0.835    0.846
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   mhc_sf ~
##     extrnl_dnt (a)    4.587    1.239    3.703    0.000    3.961    0.308
##     internl_vl (b)   -1.198    0.990   -1.210    0.226   -1.297   -0.101
##     negtv_vnts (c)   -4.821    1.472   -3.276    0.001   -3.875   -0.302
##   resilience ~
##     extrnl_dnt (d)    0.192    0.067    2.881    0.004    0.250    0.250
##     internl_vl (e)   -0.078    0.054   -1.450    0.147   -0.127   -0.127
##     negtv_vnts (f)   -0.231    0.080   -2.887    0.004   -0.279   -0.279
##
## Covariances:
##                        Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   external_identity ~~
##     internal_value        0.484    0.078    6.235    0.000    0.518    0.518
##     negative_evnts        0.277    0.059    4.675    0.000    0.398    0.398
##   internal_value ~~
##     negative_evnts        0.448    0.084    5.323    0.000    0.514    0.514
##  .resilience ~~
##    .mhc_sf                2.474    0.532    4.653    0.000    3.933    0.326
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        5.067    0.051   99.249    0.000    5.067    5.260
##    .cnsdr_ath         5.876    0.059   99.896    0.000    5.876    5.294
##    .sprt_impt         5.110    0.080   63.963    0.000    5.110    3.390
##    .think_sprt        4.904    0.081   60.577    0.000    4.904    3.211
##    .dprs_sprt         5.666    0.066   85.293    0.000    5.666    4.521
##    .bad_sprt          5.506    0.076   72.198    0.000    5.506    3.826
##    .bounce            3.953    0.050   78.695    0.000    3.953    4.374
##    .strs_evnt         3.350    0.060   55.917    0.000    3.350    3.106
##    .strs_rcvr         3.565    0.055   64.528    0.000    3.565    3.588
##    .snap_back         3.521    0.056   63.056    0.000    3.521    3.502
##    .difficult         3.372    0.055   61.215    0.000    3.372    3.404
##    .setbacks          3.577    0.055   65.263    0.000    3.577    3.624
##    .mhc_sf           32.127    0.703   45.725    0.000   32.127    2.500
##     external_dntty    0.000                               0.000    0.000
##     internal_value    0.000                               0.000    0.000
##     negative_evnts    0.000                               0.000    0.000
##    .resilience        0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        0.183    0.075    2.439    0.015    0.183    0.197
##    .cnsdr_ath         0.657    0.075    8.749    0.000    0.657    0.534
##    .sprt_impt         1.099    0.129    8.483    0.000    1.099    0.484
##    .think_sprt        0.279    0.176    1.582    0.114    0.279    0.120
##    .dprs_sprt         0.925    0.111    8.326    0.000    0.925    0.589
##    .bad_sprt          1.006    0.162    6.227    0.000    1.006    0.486
##    .bounce            0.375    0.034   10.984    0.000    0.375    0.459
##    .strs_evnt         0.432    0.042   10.246    0.000    0.432    0.371
```

```
##    .strs_rcvr          0.532    0.047   11.425    0.000    0.532    0.539
##    .snap_back          0.349    0.035    9.952    0.000    0.349    0.345
##    .difficult          0.567    0.049   11.632    0.000    0.567    0.578
##    .setbacks           0.278    0.031    9.049    0.000    0.278    0.285
##    .mhc_sf           145.189   12.260   11.842    0.000  145.189    0.879
##     external_dntty    0.745    0.100    7.428    0.000    1.000    1.000
##     internal_value    1.173    0.179    6.538    0.000    1.000    1.000
##     negative_evnts    0.646    0.129    5.016    0.000    1.000    1.000
##    .resilience         0.396    0.055    7.132    0.000    0.895    0.895
```

```
# graph looks cleaner
semPaths(basic_athlete_sem_fit,
         what = "paths",
         whatLabels = "std",
         reorder = FALSE,
         layout = "tree3",
         rotation = 4,
         intercepts = FALSE)
```




```
athlete_sem <- '
  # measurement model
    external_identity =~ sprt_goals + cnsdr_ath
    internal_value =~ sprt_impt + think_sprt
    negative_events =~ dprs_sprt + bad_sprt

    athlete_identity =~ external_identity + internal_value + negative_events
```

```
    resilience =~ bounce + strs_evnt + strs_rcvr + snap_back + difficult + setbacks

  # structural model - direct effects
    mhc_sf ~ a*athlete_identity + c*resilience + e*age_grp
    resilience ~ d*athlete_identity
    age_grp ~ g*athlete_identity

  # indirect
    indirect_athlete_identity := d*c + g*e

  # total
    total_athlete_identity:= d*c + a
'

athletes <- athletes %>% map_df(., as.numeric())

athlete_sem_fit <- sem(athlete_sem,
                       data = athletes,
                       sample.cov = TRUE,
                       missing = "ML")
# standardized
summary(athlete_sem_fit, standardized = TRUE)
```

```
## lavaan 0.6-10 ended normally after 109 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        48
##
##   Number of observations                           363
##   Number of missing patterns                         4
##
## Model Test User Model:
##
##   Test statistic                               142.309
##   Degrees of freedom                                71
##   P-value (Chi-square)                           0.000
##
## 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
##   external_identity =~
##     sprt_goals          1.000                               0.862    0.895
##     cnsdr_ath           0.880    0.114    7.730    0.000    0.759    0.684
##   internal_value =~
##     sprt_impt           1.000                               1.076    0.714
##     think_sprt          1.340    0.142    9.461    0.000    1.442    0.944
##   negative_events =~
##     dprs_sprt           1.000                               0.778    0.621
```

```
##     bad_sprt             1.370    0.201    6.804    0.000    1.065    0.741
##   athlete_identity =~
##     external_dntty       1.000                               0.619    0.619
##     internal_value       1.473    0.243    6.057    0.000    0.730    0.730
##     negative_evnts       1.072    0.211    5.081    0.000    0.735    0.735
##   resilience =~
##     bounce               1.000                               0.664    0.735
##     strs_evnt            1.284    0.093   13.747    0.000    0.853    0.792
##     strs_rcvr            1.016    0.085   11.916    0.000    0.675    0.679
##     snap_back            1.224    0.087   14.137    0.000    0.813    0.810
##     difficult            0.968    0.086   11.222    0.000    0.643    0.650
##     setbacks             1.252    0.085   14.735    0.000    0.832    0.844
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   mhc_sf ~
##     athlt_dntt (a)    0.195    1.679    0.116    0.908    0.104    0.008
##     resilience (c)    7.525    1.133    6.644    0.000    4.997    0.390
##     age_grp    (e)    1.257    0.557    2.256    0.024    1.257    0.123
##   resilience ~
##     athlt_dntt (d)   -0.193    0.098   -1.975    0.048   -0.155   -0.155
##   age_grp ~
##     athlt_dntt (g)   -0.730    0.197   -3.711    0.000   -0.390   -0.311
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        5.067    0.051   99.278    0.000    5.067    5.260
##    .cnsdr_ath         5.876    0.059   99.909    0.000    5.876    5.294
##    .sprt_impt         5.108    0.080   63.974    0.000    5.108    3.390
##    .think_sprt        4.903    0.081   60.599    0.000    4.903    3.210
##    .dprs_sprt         5.665    0.066   85.306    0.000    5.665    4.520
##    .bad_sprt          5.504    0.076   72.213    0.000    5.504    3.826
##    .bounce            3.954    0.050   78.719    0.000    3.954    4.379
##    .strs_evnt         3.352    0.060   55.944    0.000    3.352    3.111
##    .strs_rcvr         3.566    0.055   64.551    0.000    3.566    3.592
##    .snap_back         3.523    0.056   63.083    0.000    3.523    3.508
##    .difficult         3.373    0.055   61.238    0.000    3.373    3.408
##    .setbacks          3.579    0.055   65.291    0.000    3.579    3.630
##    .mhc_sf           28.739    1.656   17.356    0.000   28.739    2.242
##    .age_grp           2.689    0.066   40.958    0.000    2.689    2.150
##    .external_dntty    0.000                               0.000    0.000
##    .internal_value    0.000                               0.000    0.000
##    .negative_evnts    0.000                               0.000    0.000
##     athlete_idntty    0.000                               0.000    0.000
##    .resilience        0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .sprt_goals        0.185    0.088    2.099    0.036    0.185    0.199
##    .cnsdr_ath         0.656    0.083    7.874    0.000    0.656    0.533
##    .sprt_impt         1.113    0.135    8.221    0.000    1.113    0.490
##    .think_sprt        0.254    0.192    1.319    0.187    0.254    0.109
##    .dprs_sprt         0.965    0.110    8.808    0.000    0.965    0.615
##    .bad_sprt          0.935    0.170    5.511    0.000    0.935    0.452
```

```
##    .bounce            0.374    0.034   10.971    0.000    0.374    0.459
##    .strs_evnt         0.433    0.042   10.248    0.000    0.433    0.373
##    .strs_rcvr         0.531    0.046   11.414    0.000    0.531    0.538
##    .snap_back         0.347    0.035    9.928    0.000    0.347    0.344
##    .difficult         0.566    0.049   11.626    0.000    0.566    0.578
##    .setbacks          0.280    0.031    9.093    0.000    0.280    0.288
##    .mhc_sf          136.344   10.886   12.525    0.000  136.344    0.830
##    .age_grp           1.413    0.116   12.222    0.000    1.413    0.903
##    .external_dntty    0.459    0.099    4.614    0.000    0.617    0.617
##    .internal_value    0.542    0.122    4.439    0.000    0.468    0.468
##    .negative_evnts    0.278    0.090    3.085    0.002    0.460    0.460
##     athlete_idntty    0.284    0.067    4.256    0.000    1.000    1.000
##    .resilience        0.430    0.059    7.317    0.000    0.976    0.976
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     indrct_thlt_dn   -2.373    0.932   -2.545    0.011   -1.265   -0.099
##     ttl_thlt_dntty   -1.260    1.821   -0.692    0.489   -0.672   -0.052
```

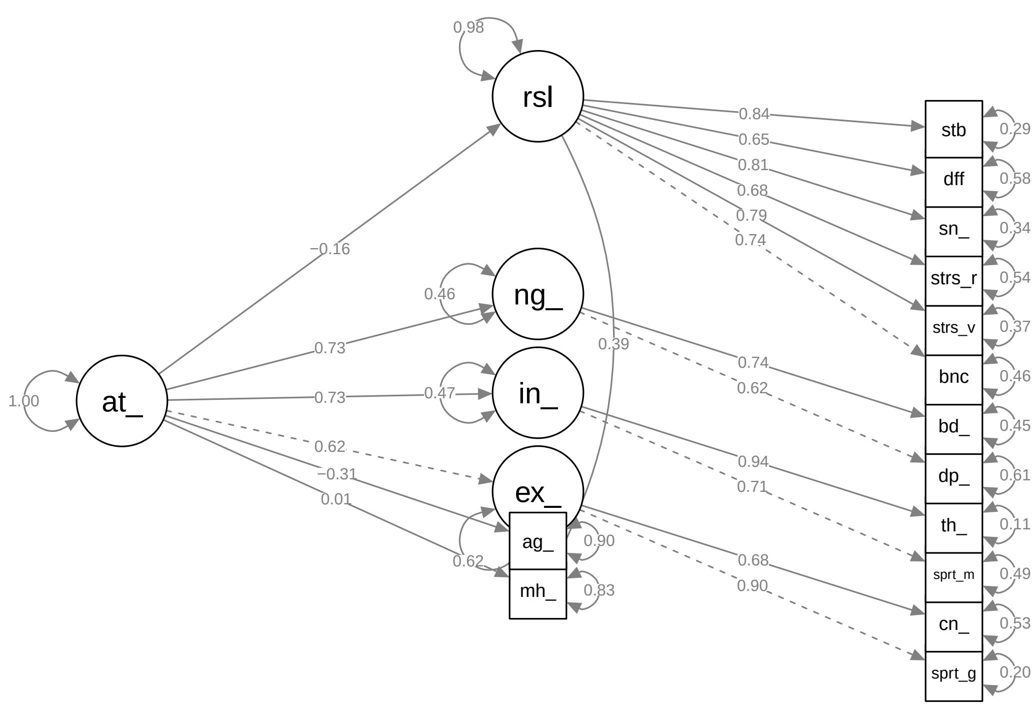
```
# unstandardized
summary(athlete_sem_fit)
```

```
## lavaan 0.6-10 ended normally after 109 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        48
##
##   Number of observations                           363
##   Number of missing patterns                         4
##
## Model Test User Model:
##
##   Test statistic                               142.309
##   Degrees of freedom                                71
##   P-value (Chi-square)                           0.000
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Observed
##   Observed information based on                Hessian
##
## Latent Variables:
##                        Estimate  Std.Err  z-value  P(>|z|)
##   external_identity =~
##     sprt_goals            1.000
##     cnsdr_ath             0.880    0.114    7.730    0.000
##   internal_value =~
##     sprt_impt             1.000
##     think_sprt            1.340    0.142    9.461    0.000
##   negative_events =~
##     dprs_sprt             1.000
##     bad_sprt              1.370    0.201    6.804    0.000
##   athlete_identity =~
```

```
##     external_dntty        1.000
##     internal_value        1.473    0.243    6.057    0.000
##     negative_evnts        1.072    0.211    5.081    0.000
##   resilience =~
##     bounce                1.000
##     strs_evnt             1.284    0.093   13.747    0.000
##     strs_rcvr             1.016    0.085   11.916    0.000
##     snap_back             1.224    0.087   14.137    0.000
##     difficult             0.968    0.086   11.222    0.000
##     setbacks              1.252    0.085   14.735    0.000
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   mhc_sf ~
##     athlt_dntt (a)    0.195    1.679    0.116    0.908
##     resilience (c)    7.525    1.133    6.644    0.000
##     age_grp    (e)    1.257    0.557    2.256    0.024
##   resilience ~
##     athlt_dntt (d)   -0.193    0.098   -1.975    0.048
##   age_grp ~
##     athlt_dntt (g)   -0.730    0.197   -3.711    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .sprt_goals        5.067    0.051   99.278    0.000
##    .cnsdr_ath         5.876    0.059   99.909    0.000
##    .sprt_impt         5.108    0.080   63.974    0.000
##    .think_sprt        4.903    0.081   60.599    0.000
##    .dprs_sprt         5.665    0.066   85.306    0.000
##    .bad_sprt          5.504    0.076   72.213    0.000
##    .bounce            3.954    0.050   78.719    0.000
##    .strs_evnt         3.352    0.060   55.944    0.000
##    .strs_rcvr         3.566    0.055   64.551    0.000
##    .snap_back         3.523    0.056   63.083    0.000
##    .difficult         3.373    0.055   61.238    0.000
##    .setbacks          3.579    0.055   65.291    0.000
##    .mhc_sf           28.739    1.656   17.356    0.000
##    .age_grp           2.689    0.066   40.958    0.000
##    .external_dntty    0.000
##    .internal_value    0.000
##    .negative_evnts    0.000
##     athlete_idntty    0.000
##    .resilience        0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .sprt_goals        0.185    0.088    2.099    0.036
##    .cnsdr_ath         0.656    0.083    7.874    0.000
##    .sprt_impt         1.113    0.135    8.221    0.000
##    .think_sprt        0.254    0.192    1.319    0.187
##    .dprs_sprt         0.965    0.110    8.808    0.000
##    .bad_sprt          0.935    0.170    5.511    0.000
##    .bounce            0.374    0.034   10.971    0.000
##    .strs_evnt         0.433    0.042   10.248    0.000
```

```
##    .strs_rcvr         0.531    0.046   11.414    0.000
##    .snap_back         0.347    0.035    9.928    0.000
##    .difficult         0.566    0.049   11.626    0.000
##    .setbacks          0.280    0.031    9.093    0.000
##    .mhc_sf          136.344   10.886   12.525    0.000
##    .age_grp           1.413    0.116   12.222    0.000
##    .external_dntty    0.459    0.099    4.614    0.000
##    .internal_value    0.542    0.122    4.439    0.000
##    .negative_evnts    0.278    0.090    3.085    0.002
##     athlete_idntty    0.284    0.067    4.256    0.000
##    .resilience        0.430    0.059    7.317    0.000
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     indrct_thlt_dn   -2.373    0.932   -2.545    0.011
##     ttl_thlt_dntty   -1.260    1.821   -0.692    0.489
```

```
# graph looks cleaner
semPaths(athlete_sem_fit,
         what = "paths",
         whatLabels = "std",
         reorder = FALSE,
         layout = "tree2",
         rotation = 2,
         intercepts = FALSE)
```



```r
athletes$age_grp %>% as.numeric()
```

```
##   [1] 3 1 1 3 4 4 3 3 1 4 2 3 5 1 5 2 2 2 2 2 2 5 1 1 1 4 2 2 2 3 4 1 3 1 4 5 1
##  [38] 2 2 3 1 1 1 3 2 3 2 4 1 2 1 1 3 2 1 1 3 2 1 3 1 1 1 3 4 5 5 4 3 4 2 3 3 1
##  [75] 5 1 1 4 1 2 3 1 4 1 6 2 1 3 2 2 3 2 4 1 2 5 1 2 4 2 4 3 6 1 5 4 3 2 3 2 5
## [112] 3 2 3 3 4 2 4 4 2 2 3 4 4 3 3 4 4 3 3 2 2 2 4 2 5 2 4 5 3 3 1 2 3 4 5 4 4
## [149] 2 3 2 2 2 5 4 4 4 5 3 5 4 4 6 1 4 2 2 1 3 4 2 5 6 2 1 1 2 2 2 2 3 3 4 5 2
## [186] 3 2 1 4 2 3 2 2 2 3 2 4 1 2 2 2 3 2 2 2 2 2 2 2 2 4 1 3 2 2 3 3 4 3 3 4 1 2
## [223] 1 3 3 7 4 2 4 3 4 4 4 4 5 4 4 2 3 3 4 2 2 3 2 4 4 3 2 2 3 4 2 4 2 2 3 3 2
## [260] 3 3 3 2 3 3 2 2 2 2 3 3 2 2 2 2 2 3 2 1 3 5 2 2 3 4 4 3 3 4 3 1 2 4 2 2 2
## [297] 3 2 3 2 2 3 5 3 3 3 1 2 1 1 2 1 1 1 1 1 1 2 1 6 1 3 2 2 3 3 4 2 2 2 2 2 2
## [334] 3 2 2 2 7 3 1 4 2 6 2 2 6 3 2 4 1 2 1 1 1 3 3 2 2 3 2 2 2 2 2
```

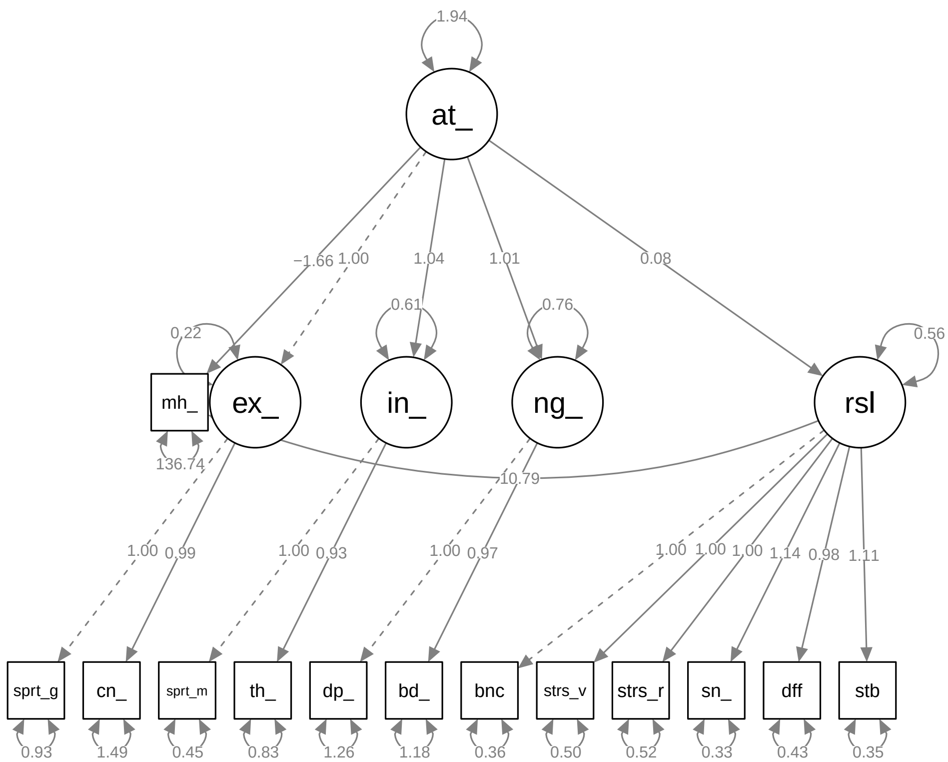
```r
non_athlete_sem <- '
  # measurement model
    external_identity =~ sprt_goals + cnsdr_ath
    internal_value =~ sprt_impt + think_sprt
    negative_events =~ dprs_sprt + bad_sprt

    athlete_identity =~ external_identity + internal_value + negative_events

    resilience =~ bounce + strs_evnt + strs_rcvr + snap_back + difficult + setbacks

  # structural model - direct effects
    mhc_sf ~ a*athlete_identity + c*resilience
    resilience ~ d*athlete_identity

  # indirect
    indirect_athlete_identity := d*c

  # total
    total_athlete_identity:= d*c + a
'

non_athlete_sem_fit <- sem(non_athlete_sem,
                       data = non_athletes,
                       sample.cov = TRUE,
                       missing = "ML")

# unstandardized
summary(non_athlete_sem_fit)
```

```
## lavaan 0.6-10 ended normally after 89 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        44
##
##                                                   Used       Total
##   Number of observations                           373         390
##   Number of missing patterns                         5
##
## Model Test User Model:
##
```

```
##   Test statistic                                78.029
##   Degrees of freedom                                60
##   P-value (Chi-square)                           0.059
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Observed
##   Observed information based on                Hessian
##
## Latent Variables:
##                        Estimate  Std.Err  z-value  P(>|z|)
##   external_identity =~
##     sprt_goals            1.000
##     cnsdr_ath             0.987    0.099    9.942    0.000
##   internal_value =~
##     sprt_impt             1.000
##     think_sprt            0.931    0.067   13.848    0.000
##   negative_events =~
##     dprs_sprt             1.000
##     bad_sprt              0.972    0.094   10.288    0.000
##   athlete_identity =~
##     external_dntty        1.000
##     internal_value        1.041    0.107    9.714    0.000
##     negative_evnts        1.013    0.120    8.462    0.000
##   resilience =~
##     bounce                1.000
##     strs_evnt             1.000    0.071   14.050    0.000
##     strs_rcvr             1.001    0.071   14.096    0.000
##     snap_back             1.143    0.069   16.448    0.000
##     difficult             0.975    0.066   14.664    0.000
##     setbacks              1.111    0.068   16.247    0.000
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   mhc_sf ~
##     athlt_dntt (a)   -1.657    0.780   -2.124    0.034
##     resilience (c)   10.787    1.052   10.251    0.000
##   resilience ~
##     athlt_dntt (d)    0.077    0.049    1.579    0.114
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .sprt_goals        4.288    0.139   30.913    0.000
##    .cnsdr_ath         3.412    0.150   22.819    0.000
##    .sprt_impt         3.805    0.141   27.057    0.000
##    .think_sprt        3.345    0.141   23.734    0.000
##    .dprs_sprt         4.275    0.158   27.071    0.000
##    .bad_sprt          4.042    0.153   26.373    0.000
##    .bounce            3.766    0.052   72.147    0.000
##    .strs_evnt         3.262    0.056   58.262    0.000
##    .strs_rcvr         3.401    0.057   59.928    0.000
##    .snap_back         3.339    0.056   59.522    0.000
##    .difficult         3.280    0.053   61.469    0.000
```

```
##    .setbacks          3.427    0.056   61.507    0.000
##    .mhc_sf           35.009    0.757   46.223    0.000
##    .external_dntty    0.000
##    .internal_value    0.000
##    .negative_evnts    0.000
##     athlete_idntty    0.000
##    .resilience        0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .sprt_goals        0.927    0.184    5.040    0.000
##    .cnsdr_ath         1.489    0.222    6.698    0.000
##    .sprt_impt         0.453    0.142    3.202    0.001
##    .think_sprt        0.832    0.147    5.644    0.000
##    .dprs_sprt         1.259    0.241    5.220    0.000
##    .bad_sprt          1.177    0.227    5.184    0.000
##    .bounce            0.357    0.033   10.804    0.000
##    .strs_evnt         0.495    0.043   11.449    0.000
##    .strs_rcvr         0.523    0.045   11.528    0.000
##    .snap_back         0.326    0.033    9.884    0.000
##    .difficult         0.426    0.038   11.275    0.000
##    .setbacks          0.352    0.034   10.319    0.000
##    .mhc_sf          136.741   11.592   11.796    0.000
##    .external_dntty    0.219    0.181    1.210    0.226
##    .internal_value    0.614    0.196    3.134    0.002
##    .negative_evnts    0.759    0.231    3.286    0.001
##     athlete_idntty    1.943    0.351    5.536    0.000
##    .resilience        0.564    0.068    8.254    0.000
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     indrct_thlt_dn    0.833    0.545    1.527    0.127
##     ttl_thlt_dntty   -0.824    0.866   -0.951    0.341
```

```r
# graph looks cleaner
semPaths(non_athlete_sem_fit,
         what = "paths",
         whatLabels = "est",
         reorder = FALSE,
         layout = "tree2",
         rotation = 1,
         intercepts = FALSE)
```



Interpretation

From our SEM, we observe that athlete identity *negatively* affects emotional well being, as defined by the MHC-SF scale. Resilience is associated with a positive effect on MHC-SF.