Mo' Bias

Let's at bivariate correlations among the proposed bias metrics just within the happy stimuli, since we have evidence that happy faces have good internal reliability as compared to sad faces.

```
library(tidyverse); library(corxplor); library(parallel)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.2.1 --
## √ ggplot2 2.2.1     √ purrr   0.2.4
## √ tibble  1.4.2     √ dplyr   0.7.4
## √ tidyr   0.7.2     √ stringr 1.2.0
## √ readr   1.1.1     √ forcats 0.2.0
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
bias_summary <- read_csv("~/Box Sync/MDL Projects/Projects/R56 Mood and Brain Study/Data/Eye tracking da
```

```
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   id = col_integer(),
##   bdi = col_integer(),
##   emo_valence = col_character(),
##   n_dp_valid_1 = col_integer(),
##   n_gaze_valid_1 = col_integer(),
##   n_dp_valid_2 = col_integer(),
##   n_gaze_valid_2 = col_integer(),
##   depressed = col_character()
## )
## See spec(...) for full column specifications.
```

```
happy <- bias_summary %>% filter(emo_valence == "Happy") %>%
   select(dp_bias_1, pct_dp_toward_1:final_gaze_bias_1,
          pct_gaze_toward_1:var_gaze_bias_1)
bias_cors <- cor_test(happy, method = "spearman")
```

Mean Toward

The "mean bias toward" is a bit of a misnomer given that the strongest predictors of this construct, for both the TLBS and trial-level fixation metrics, are variability and "mean bias away". These metrics are simply reflecting the tendency for participants to show strong reactions both toward and away from emotional stimuli and/or highly variable attention and RTs. It cannot be taken as evidence of a negative attention bias as it is traditionally conceived because it is highly correlated with the metric that is supposed to be an indicator of positive attention bias.

Dot Probe

```
summary(bias_cors, mean_dp_toward_1)
```

```
##                                correlates   rho   n     p
##       mean_dp_toward_1 <-> var_dp_bias_1  0.87 169 <.001
##      mean_dp_toward_1 <-> mean_dp_away_1  0.59 169 <.001
##  mean_dp_toward_1 <-> pct_strong_toward_1  0.39 169 <.001
##    mean_dp_toward_1 <-> pct_gaze_toward_1  0.38 169 <.001
##     mean_dp_toward_1 <-> var_gaze_bias_1  0.36 169 <.001
##    mean_dp_toward_1 <-> pct_strong_away_1  0.28 169 <.001
##         mean_dp_toward_1 <-> gaze_bias_1  0.23 169  .006
##   mean_dp_toward_1 <-> mean_gaze_toward_1  0.20 169  .017
##    mean_dp_toward_1 <-> final_gaze_bias_1  0.20 169  .021
##           mean_dp_toward_1 <-> dp_bias_1  0.19 169   .03
##     mean_dp_toward_1 <-> pct_gaze_away_1  0.17 169  .044
##    mean_dp_toward_1 <-> mean_gaze_away_1  0.17 169  .045
##     mean_dp_toward_1 <-> pct_dp_toward_1  0.15 169  .081
##       mean_dp_toward_1 <-> pct_dp_away_1 -0.15 169  .081
##    mean_dp_toward_1 <-> init_gaze_bias_1  0.04 169  .652
```

Eye Tracking

```r
summary(bias_cors, mean_gaze_toward_1)
```

```
##                                  correlates   rho   n     p
##     mean_gaze_toward_1 <-> var_gaze_bias_1  0.78 169 <.001
##    mean_gaze_toward_1 <-> mean_gaze_away_1  0.78 169 <.001
##  mean_gaze_toward_1 <-> pct_strong_toward_1  0.73 169 <.001
##    mean_gaze_toward_1 <-> pct_strong_away_1  0.52 169 <.001
##         mean_gaze_toward_1 <-> gaze_bias_1  0.46 169 <.001
##    mean_gaze_toward_1 <-> final_gaze_bias_1  0.32 169 <.001
##    mean_gaze_toward_1 <-> mean_dp_toward_1  0.20 169  .017
##     mean_gaze_toward_1 <-> pct_gaze_away_1 -0.19 169  .028
##    mean_gaze_toward_1 <-> init_gaze_bias_1  0.16 169  .056
##       mean_gaze_toward_1 <-> var_dp_bias_1  0.16 169  .056
##    mean_gaze_toward_1 <-> pct_gaze_toward_1  0.16 169  .057
##      mean_gaze_toward_1 <-> mean_dp_away_1  0.13 169  .127
##     mean_gaze_toward_1 <-> pct_dp_toward_1  0.11 169  .195
##       mean_gaze_toward_1 <-> pct_dp_away_1 -0.11 169  .195
##           mean_gaze_toward_1 <-> dp_bias_1  0.07 169  .392
```

Percent trials towards

Percent trials toward is perfectly negatively correlated with percent trials away in the dot probe task because it is essentially impossible to have a reaction time difference of exactly 0, whereas it is possible to never fixate on either the emotional or neutral stimulus.

For the dot probe, this metric tracks highly with the traditional bias score, and both show extremely poor test-retest reliability. And it appears to be independent of variability (which did show relatively good test-retest reliability).

For gaze fixations, this metric appears to represent a blend of information about attention bias (as traditionally conceived) and attention variability, given that it is moderately correlated with both.

Dot Probe

```r
summary(bias_cors, pct_dp_toward_1)
```

```
##                               correlates   rho   n     p
##        pct_dp_toward_1 <-> pct_dp_away_1 -1.00 169 <.001
##            pct_dp_toward_1 <-> dp_bias_1  0.87 169 <.001
##    pct_dp_toward_1 <-> final_gaze_bias_1  0.34 169 <.001
##       pct_dp_toward_1 <-> mean_dp_away_1 -0.27 169 <.001
##          pct_dp_toward_1 <-> gaze_bias_1  0.18 169   .03
##     pct_dp_toward_1 <-> mean_dp_toward_1  0.15 169  .081
##     pct_dp_toward_1 <-> init_gaze_bias_1  0.14 169  .097
##      pct_dp_toward_1 <-> pct_gaze_away_1 -0.13 169  .127
##   pct_dp_toward_1 <-> mean_gaze_toward_1  0.11 169  .195
##  pct_dp_toward_1 <-> pct_strong_toward_1  0.11 169  .218
##    pct_dp_toward_1 <-> pct_gaze_toward_1  0.11 169  .218
##        pct_dp_toward_1 <-> var_dp_bias_1 -0.09 169  .298
##     pct_dp_toward_1 <-> mean_gaze_away_1  0.08 169  .353
##      pct_dp_toward_1 <-> var_gaze_bias_1  0.05 169  .552
##    pct_dp_toward_1 <-> pct_strong_away_1 -0.02 169  .805
```

Eye Tracking

```r
summary(bias_cors, pct_gaze_toward_1)
```

```
##                                 correlates   rho   n     p
##  pct_gaze_toward_1 <-> pct_strong_toward_1  0.68 169 <.001
##          pct_gaze_toward_1 <-> gaze_bias_1  0.67 169 <.001
##      pct_gaze_toward_1 <-> var_gaze_bias_1  0.46 169 <.001
##     pct_gaze_toward_1 <-> mean_dp_toward_1  0.38 169 <.001
##        pct_gaze_toward_1 <-> var_dp_bias_1  0.32 169 <.001
##     pct_gaze_toward_1 <-> init_gaze_bias_1  0.29 169 <.001
##    pct_gaze_toward_1 <-> final_gaze_bias_1  0.23 169  .006
##       pct_gaze_toward_1 <-> mean_dp_away_1  0.20 169  .018
##      pct_gaze_toward_1 <-> pct_gaze_away_1  0.20 169  .018
##    pct_gaze_toward_1 <-> pct_strong_away_1  0.19 169  .029
##   pct_gaze_toward_1 <-> mean_gaze_toward_1  0.16 169  .057
##            pct_gaze_toward_1 <-> dp_bias_1  0.16 169  .067
##      pct_gaze_toward_1 <-> pct_dp_toward_1  0.11 169  .218
##        pct_gaze_toward_1 <-> pct_dp_away_1 -0.11 169  .218
##     pct_gaze_toward_1 <-> mean_gaze_away_1 -0.02 169  .872
```

Removing the variability component from percent-trials toward/away

The percent of trials directed either toward or away from the emotional stimulus appears to represent a blend of information about attention bias and attention variability, including some aspect of task motivation since participants who are highly "on-task" will have low scores on both toward and away metrics. Perhaps we can obtain a purer metric of attention bias toward and attention bias away if we regress out the presumed variability/motivation component.

```r
happy$ab_toward_1 <- lm(pct_gaze_toward_1 ~
                          var_gaze_bias_1 + pct_gaze_away_1,
                        data = happy) %>% resid
happy$ab_away_1 <- lm(pct_gaze_away_1 ~
                        var_gaze_bias_1 + pct_gaze_toward_1,
                      data = happy) %>% resid
bias_cors <- cor_test(happy, method = "spearman")
summary(bias_cors, ab_toward_1)
```

```
##                          correlates   rho   n     p
##    ab_toward_1 <-> pct_gaze_toward_1  0.83 169 <.001
##          ab_toward_1 <-> gaze_bias_1  0.66 169 <.001
##     ab_toward_1 <-> init_gaze_bias_1  0.35 169 <.001
##  ab_toward_1 <-> pct_strong_toward_1  0.35 169 <.001
##     ab_toward_1 <-> mean_gaze_away_1 -0.33 169 <.001
##            ab_toward_1 <-> ab_away_1 -0.31 169 <.001
##    ab_toward_1 <-> final_gaze_bias_1  0.23 169  .006
##    ab_toward_1 <-> pct_strong_away_1 -0.23 169  .006
##     ab_toward_1 <-> mean_dp_toward_1  0.23 169  .007
##            ab_toward_1 <-> dp_bias_1  0.21 169  .013
##   ab_toward_1 <-> mean_gaze_toward_1 -0.18 169  .031
##        ab_toward_1 <-> var_dp_bias_1  0.16 169  .063
##      ab_toward_1 <-> pct_dp_toward_1  0.11 169  .205
##        ab_toward_1 <-> pct_dp_away_1 -0.11 169  .205
##      ab_toward_1 <-> pct_gaze_away_1 -0.04 169  .675
##       ab_toward_1 <-> mean_dp_away_1  0.03 169  .746
##      ab_toward_1 <-> var_gaze_bias_1  0.03 169  .746
```

This metric has a profile more in line with what one would expect for the construct of attention bias toward happy stimuli, with a positive correlation with overall gaze bias and negative correlations with the "away" metrics. But is it reliable? Answer: it appears to be no more or less reliable than the other fixation-based bias metrics for happy faces.

```r
ab_toward_1 <- happy$ab_toward_1
ab_toward_2 <- lm(pct_gaze_toward_2 ~
                    var_gaze_bias_2 + pct_gaze_away_2,
                  data = bias_summary %>%
                    filter(emo_valence == "Happy")) %>% resid
cor(ab_toward_1, ab_toward_2)
```

```
## [1] 0.5708944
```

Factor Analysis of Trial-level Attention Metrics

```r
library(psych)
```

```
##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

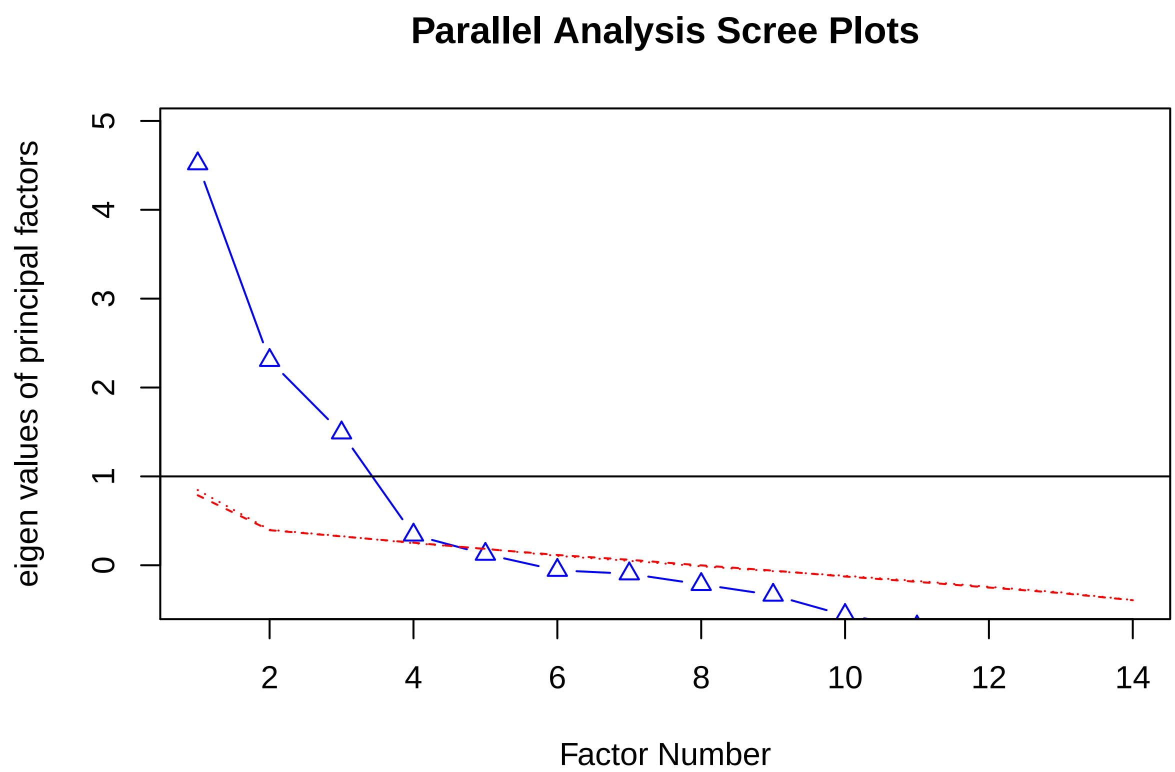
```r
fa_resample <- function(seed, object, data){
  set.seed(seed)
```

```
  i <- sample.int(nrow(data), replace = TRUE)
  fa_args <- as.list(object$Call)[-1]
  fa_args$r <- data[i,]
  fa_replicate <- suppressWarnings(do.call(fa, fa_args))
  lds <- if (object$factors == 1) fa_replicate$loadings else
    target.rot(fa_replicate$loadings, object$loadings)$loadings
  if(any(abs(lds) > 1)) lds[] <- NA_real_
  lds
}
fa_check <- function(object, data, n_rep = 1000, n_cores = 4){
  boot_ob <- mclapply(1:n_rep, fa_resample, object = object, data = data,
                      mc.cores = n_cores)
  n_fctr <- ncol(boot_ob[[1]])
  fctr_names <- colnames(object$loadings)
  lds <- map(1:n_fctr, function(i){
    map(boot_ob, ~ .[,i]) %>% transpose() %>% simplify_all() %>%
       map_dbl(~median(., na.rm = TRUE))
  })
  names(lds) <- fctr_names
  lds <- as_data_frame(lds)
  out <- map(1:n_fctr, function(i){
    prim <- lds[[i]]
    prim_boot <- map(boot_ob, ~ .[,i]) %>% transpose() %>% simplify_all()
    lwr <- prim_boot %>% map_dbl(~quantile(., .025, na.rm = TRUE))
    upr <- prim_boot %>% map_dbl(~quantile(., .975, na.rm = TRUE))
    sig <- lwr > .2 | upr < -.2
    if(ncol(lds) > 1){
      secn <- lds[,-i]
      prim_highest <- map_lgl(seq_along(prim), function(i)
        all(abs(prim[i]) > abs(secn[i,])))
      secn.3 <- map_lgl(seq_along(prim), function(i)
        all(abs(secn[i,]) <= .3))
      sig <- sig & prim_highest & secn.3
    }
      data_frame(item = names(prim_boot),
                 loadings = prim,
                 lwr = lwr,
                 upr = upr,
                 sig = sig)
    })
  names(out) <- fctr_names
  out
}
nfactors <- function(...){
    ff <- tempfile()
    png(filename=ff)
    res <- psych::nfactors(...)
    dev.off()
    unlink(ff)
    class(res) <- "nfact"
    res
}
plot.nfact <- function(object){
```

```
  data <- object$vss.stats
  data$n_factor <- 1:nrow(data)
  a <- ggplot(data, aes(x = n_factor, y = RMSEA)) +
    geom_point() + geom_line() + scale_x_continuous(breaks = 1:nrow(data)) +
    xlab("Number of Factors") +
    ggtitle("Root Mean Square Error of Approximation") + theme_bw()
  b <- ggplot(data, aes(x = n_factor, y = eBIC)) +
    geom_point() + geom_line() + scale_x_continuous(breaks = 1:nrow(data)) +
    xlab("Number of Factors") +
    ggtitle("Extended Bayesian Information Criterion") + theme_bw()
  c <- ggplot(data, aes(x = n_factor, y = cfit.1)) +
    geom_point() + geom_line() + scale_x_continuous(breaks = 1:nrow(data)) +
    xlab("Number of Factors") + ylab("Very Simple Structure Fit") +
    coord_cartesian(ylim = c(0,1)) + ggtitle("VSS Fit of Complexity 1") +
    theme_bw()
  d <- ggplot(data, aes(x = n_factor, y = cfit.2)) +
    geom_point() + geom_line() + scale_x_continuous(breaks = 1:nrow(data)) +
    xlab("Number of Factors") + ylab("Very Simple Structure Fit") +
    coord_cartesian(ylim = c(0,1)) + ggtitle("VSS Fit of Complexity 2") +
    theme_bw()
  gridExtra::grid.arrange(a,b,c,d)
}
```

The colinearity between pct_dp_toward and pct_dp_away is problematic for factor analysis. Given that both are highly correlated with traditional dot probe bias, I am dropping both. We also need to drop pct_gaze_toward and pct_gaze_away if we include the ab_toward and ab_away metrics that I just constructed, since they are linearly dependent on these metrics.

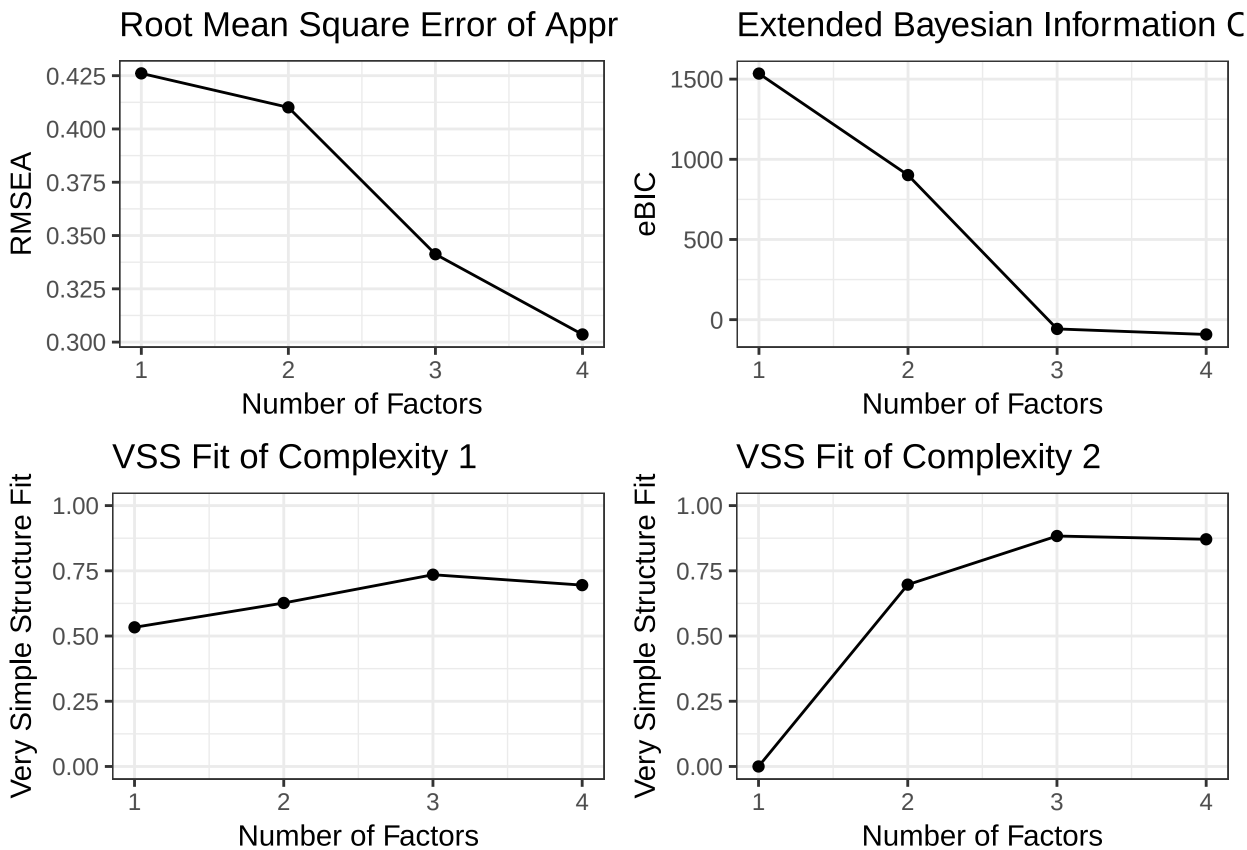
```
happy <- happy %>% select(-pct_dp_toward_1, -pct_dp_away_1,
                          -pct_gaze_toward_1, -pct_gaze_away_1)
set.seed(42)
fa.parallel(happy, fa = "fa", fm = "ml", show.legend = FALSE)
```



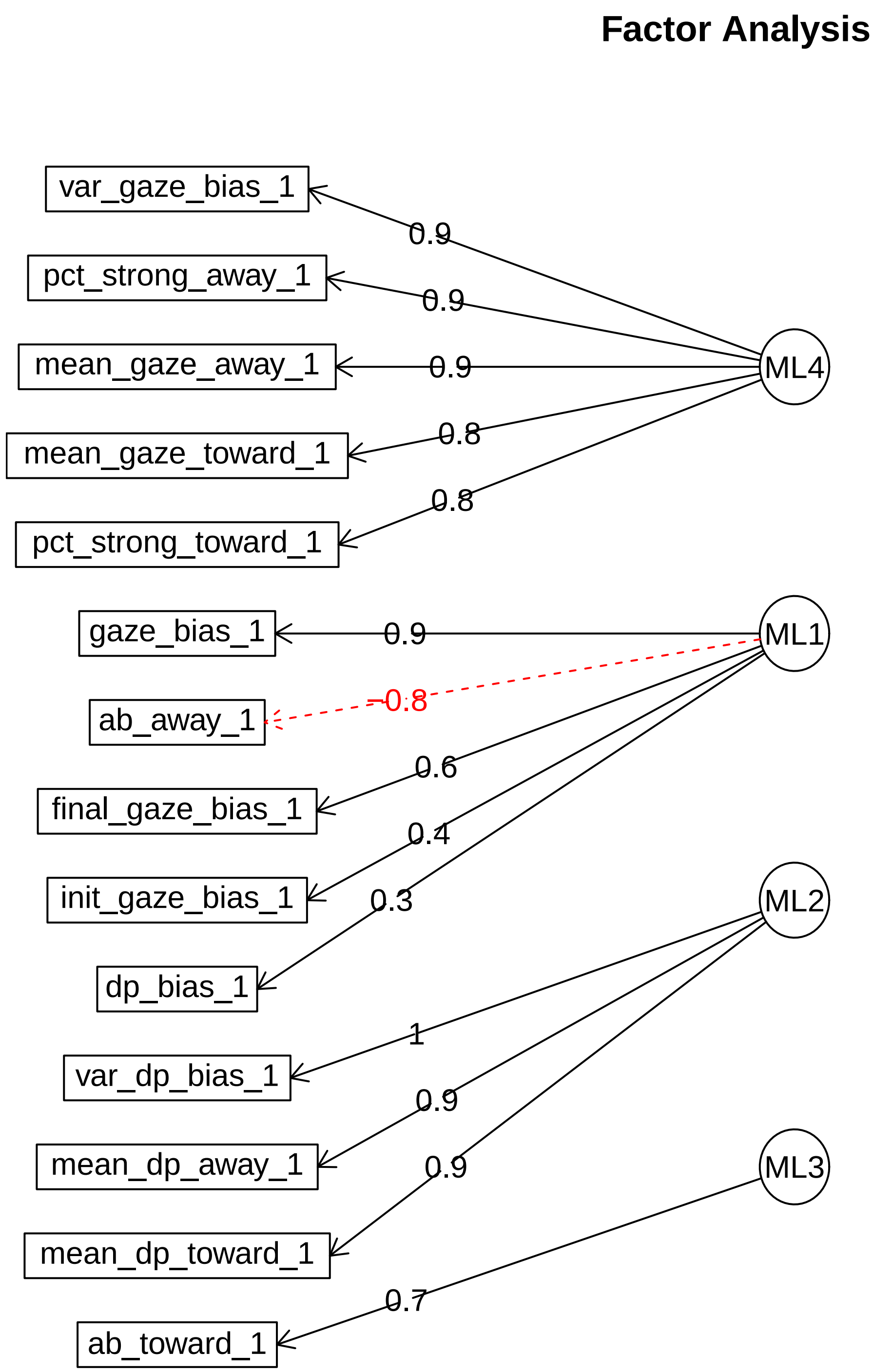

```
## Parallel analysis suggests that the number of factors =  4  and the number of components =  NA
```

Varimax Rotation with 3-4 factors

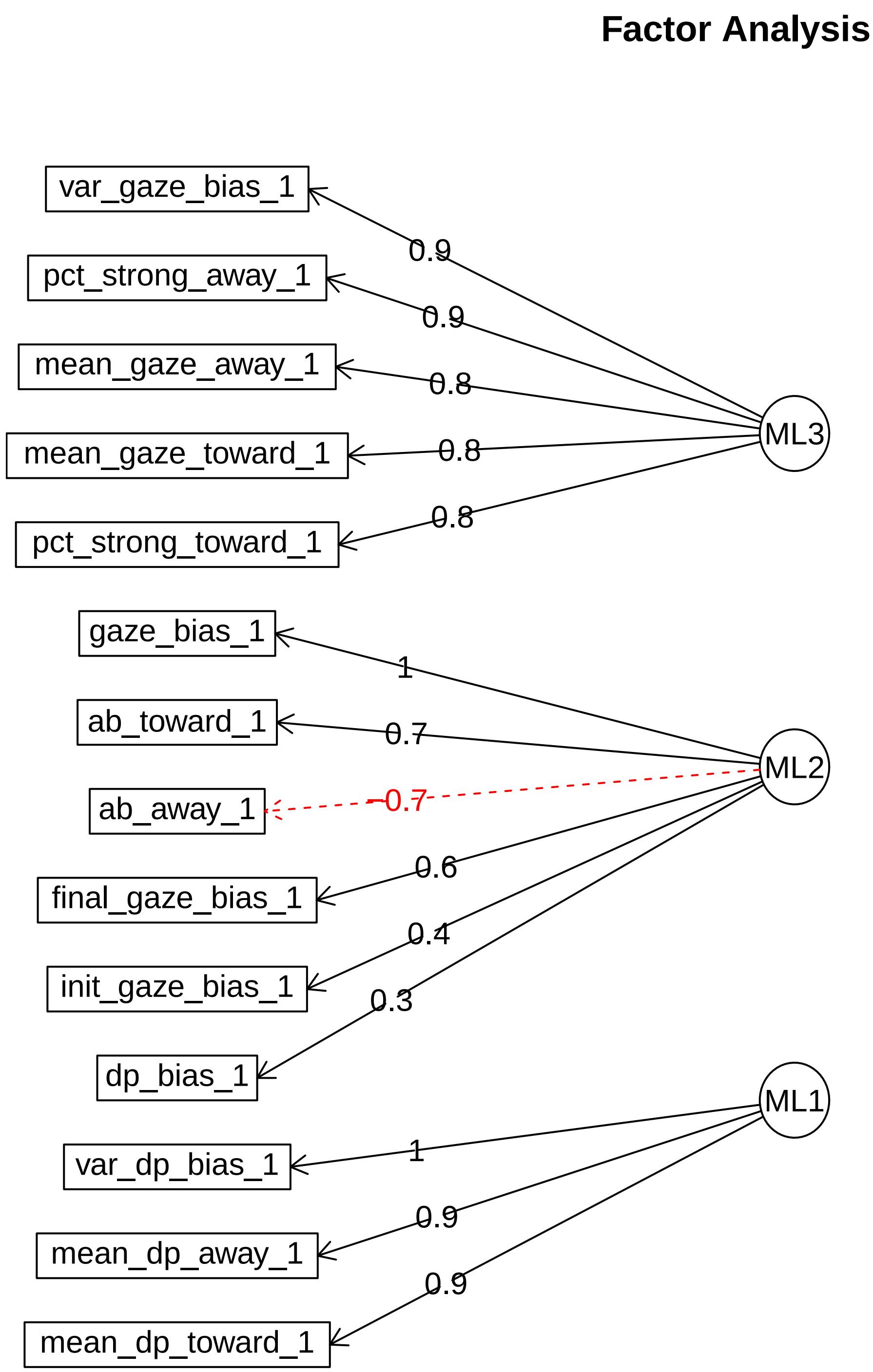
```
varmax <- nfactors(happy, n = 4, rotate = "varimax", fm = "mle")
plot(varmax)
```




```r
varmax4 <- fa(happy, nfactors = 4, fm = "ml", rotate = "varimax")
fa.diagram(varmax4)
```




```
varmax3 <- fa(happy, nfactors = 3, fm = "ml", rotate = "varimax")
fa.diagram(varmax3)
```

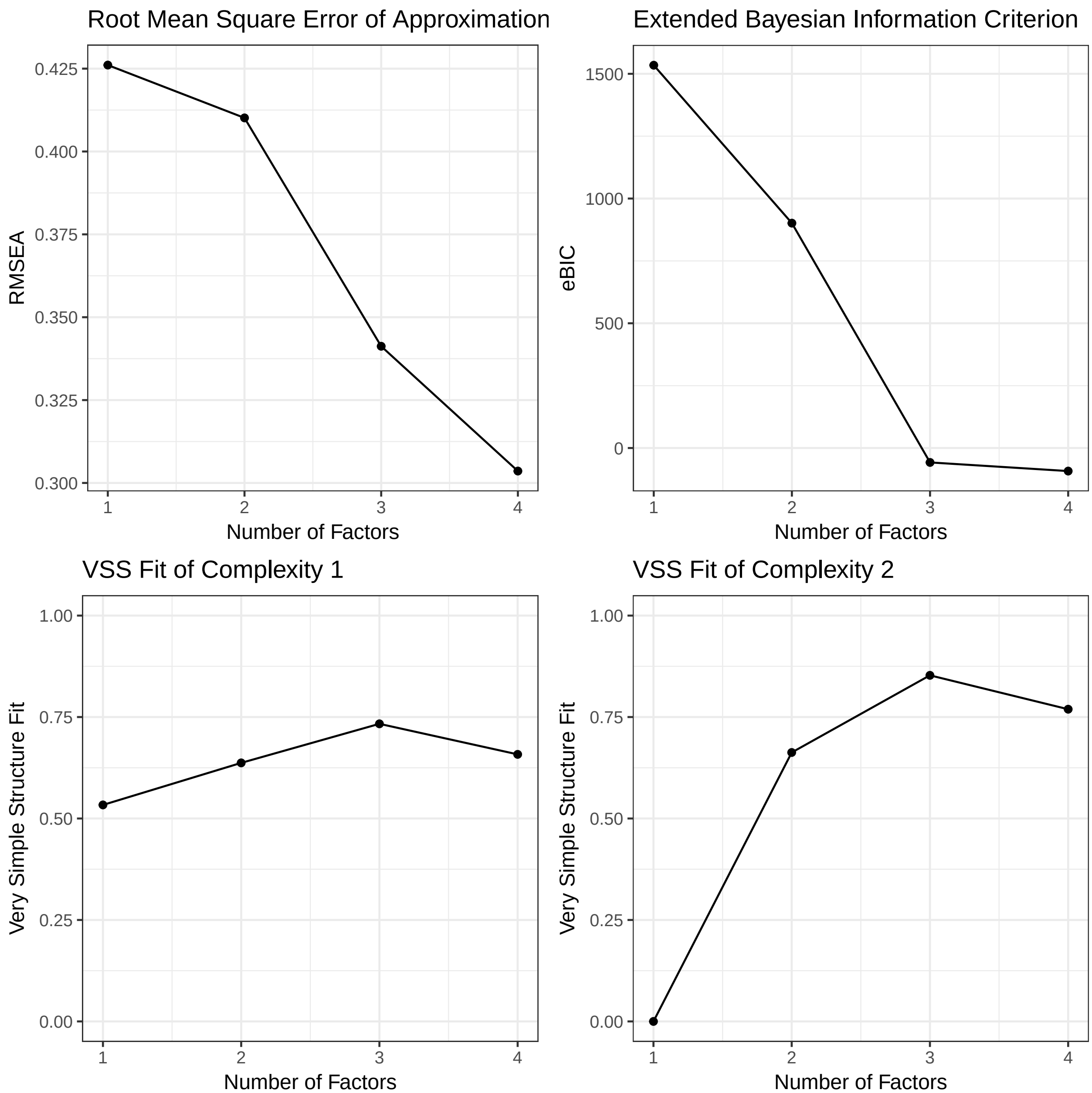


Oblimin Rotation (4 Factors)

```
oblimin <- nfactors(happy, n = 4, rotate = "oblimin", fm = "mle")
```

```
## Loading required namespace: GPArotation
```

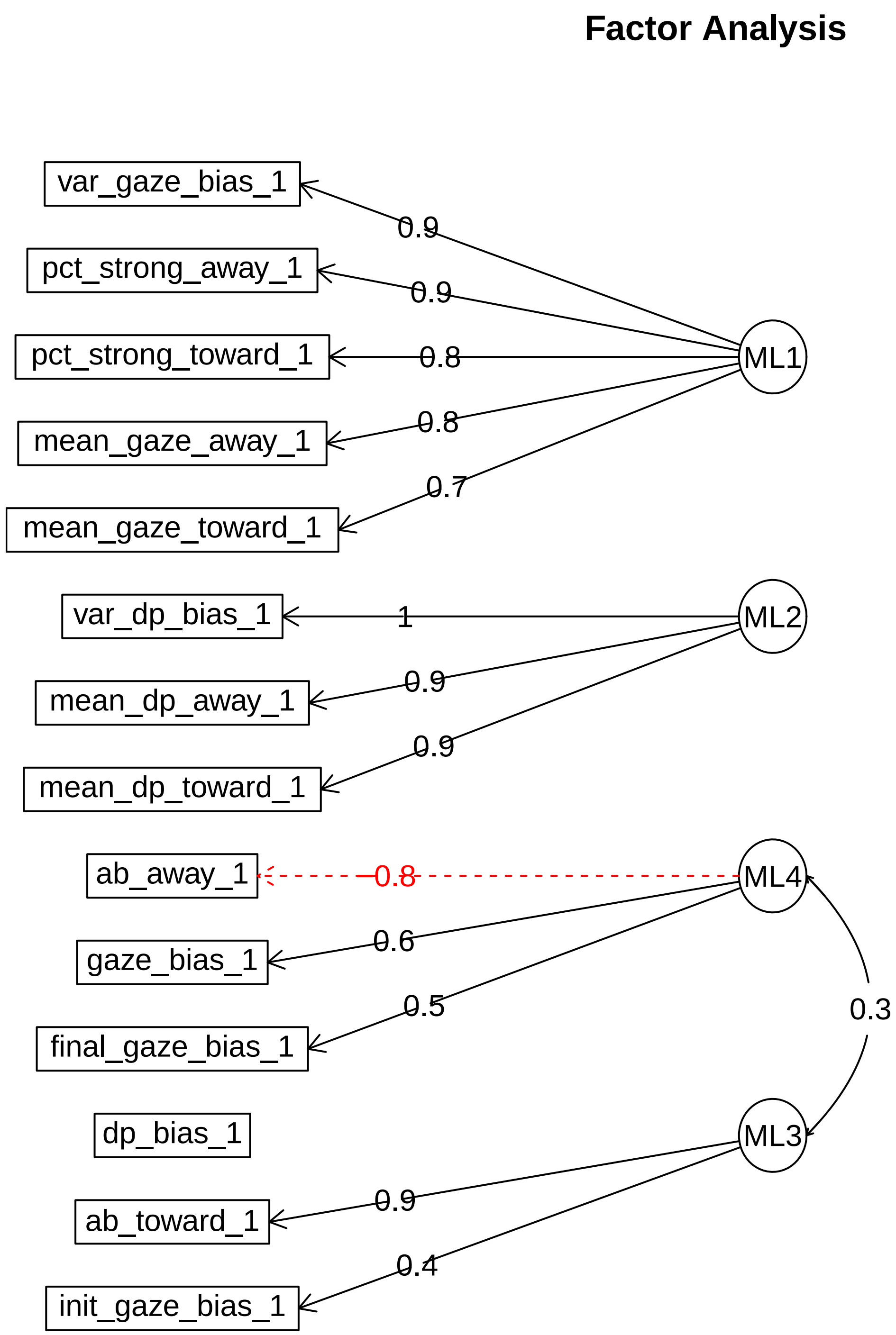
```
plot(oblimin)
```




```r
oblmin4 <- fa(happy, nfactors = 4, fm = "ml", rotate = "oblimin")
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

```r
fa.diagram(oblmin4)
```

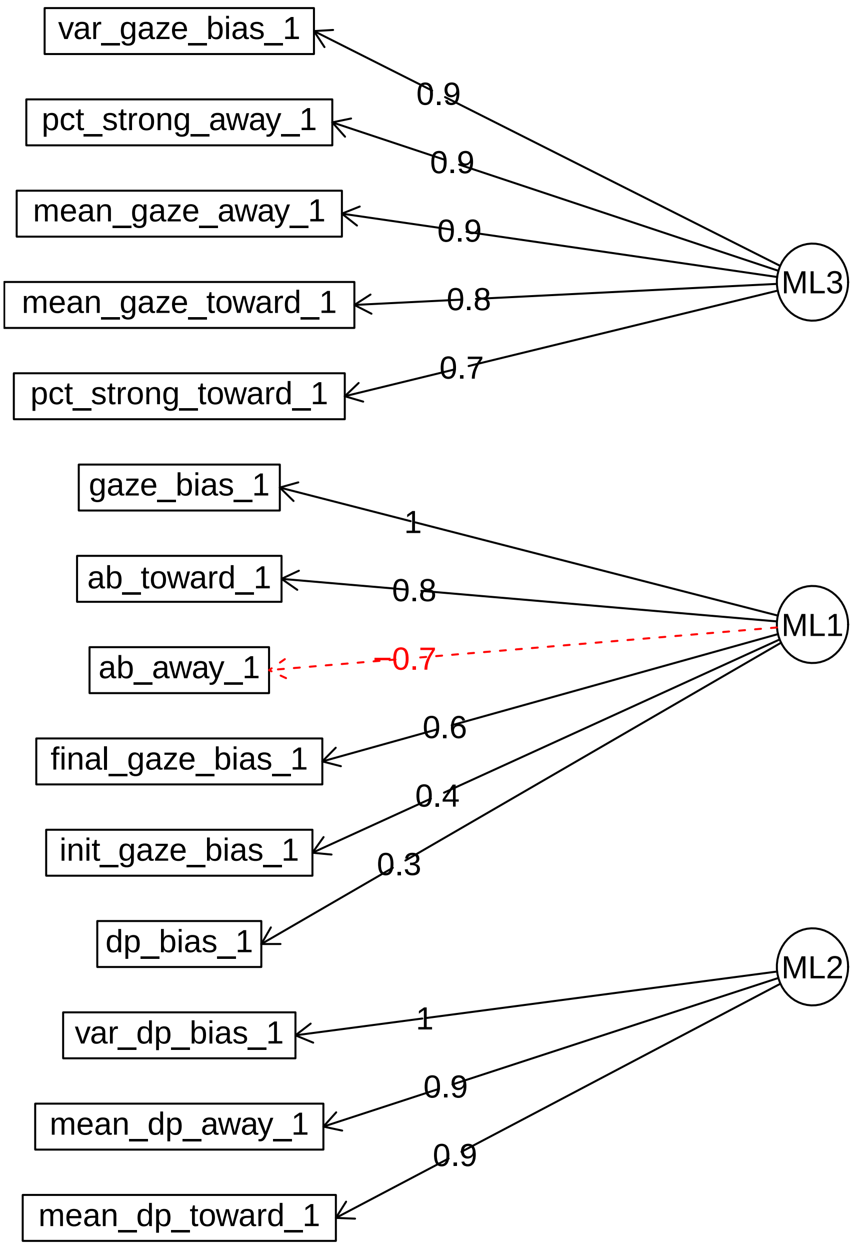



```
oblmin3 <- fa(happy, nfactors = 3, fm = "ml", rotate = "oblimin")
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

```
fa.diagram(oblmin3)
```

Factor Analysis



Exclusion of Unreliable Loadings

We next eliminated items that did not have reliably strong loadings on their primary factor (defined as a bootstrapped 95% confidence interval with a value between -.20 and .20) or did not contribute to a simple factor structure (defined as a cross-loading greater than an absolute value of .3).

```
load_confidence <- fa_check(oblmin3, happy)
names(load_confidence) <- c("fixation_variability",
                            "attention_bias",
                            "RT_variability")
loadings <- data_frame(
```

```r
  assessment = load_confidence$fixation_variability$item,
  fixation_variability = sprintf("%s%.2f [%.2f, %.2f]",
                ifelse(load_confidence$fixation_variability$sig, "*", ""),
                load_confidence$fixation_variability$loadings,
                load_confidence$fixation_variability$lwr,
                load_confidence$fixation_variability$upr),
  attention_bias = sprintf("%s%.2f [%.2f, %.2f]",
                    ifelse(load_confidence$attention_bias$sig, "*", ""),
                    load_confidence$attention_bias$loadings,
                    load_confidence$attention_bias$lwr,
                    load_confidence$attention_bias$upr),
  RT_variability = sprintf("%s%.2f [%.2f, %.2f]",
                   ifelse(load_confidence$RT_variability$sig, "*", ""),
                   load_confidence$RT_variability$loadings,
                   load_confidence$RT_variability$lwr,
                   load_confidence$RT_variability$upr),
)  %>% arrange(assessment)
sig_items <- map(load_confidence, ~ .$item[.$sig]) %>% reduce(c)
excluded_items <- setdiff(names(happy), sig_items)
excluded_items
```

```
## [1] "dp_bias_1"           "pct_strong_toward_1" "pct_strong_away_1"
```

```r
happy <- happy[sig_items]
```

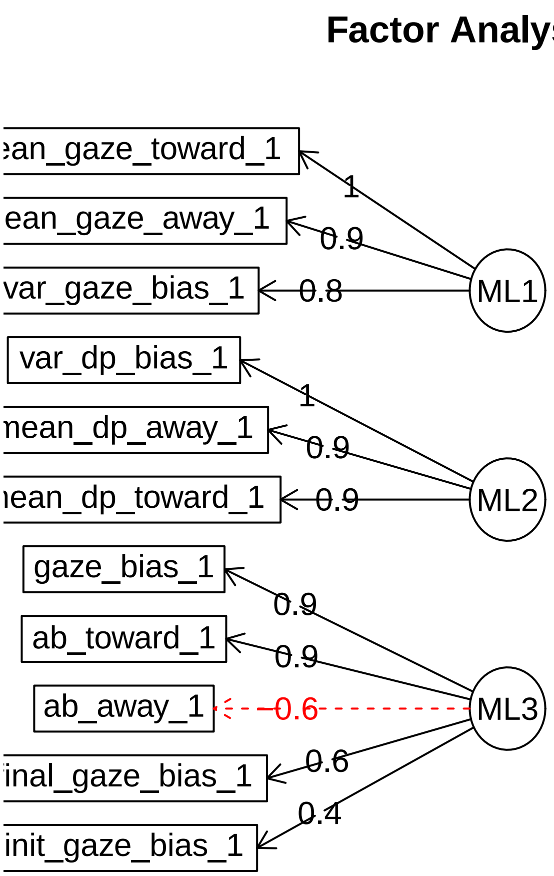
Final Stage

For the final stage, a maximum likelihood factor analysis of the remaining items using oblimin rotation yielded four factors explaining 73% of the variance. The factor loading matrix of the median and 95% confidence intervals for the loadings under random resampling are presented in the following table.

```r
oblmin3 <- fa(happy, nfactors = 3, fm = "ml", rotate = "oblimin")
oblmin3$Vaccounted %>% round(2)
```

```
##                        ML1  ML2  ML3
## SS loadings           2.75 2.68 2.66
## Proportion Var        0.25 0.24 0.24
## Cumulative Var        0.25 0.49 0.73
## Proportion Explained  0.34 0.33 0.33
## Cumulative Proportion 0.34 0.67 1.00
```

```r
fa.diagram(oblmin3)
```



There appear to be essentially 3 factors that emerge from all of these metrics: attention bias, variability in visual attention, and variability in reaction times.

```
load_confidence <- fa_check(oblmin3, happy)
names(load_confidence) <- c("fixation_variability",
                            "RT_variability",
                            "attention_bias")
loadings <- data_frame(
  assessment = load_confidence$fixation_variability$item,
  fixation_variability = sprintf("%s%.2f [%.2f, %.2f]",
                ifelse(load_confidence$fixation_variability$sig, "*", ""),
                load_confidence$fixation_variability$loadings,
                load_confidence$fixation_variability$lwr,
                load_confidence$fixation_variability$upr),
  attention_bias = sprintf("%s%.2f [%.2f, %.2f]",
                    ifelse(load_confidence$attention_bias$sig, "*", ""),
                    load_confidence$attention_bias$loadings,
                    load_confidence$attention_bias$lwr,
                    load_confidence$attention_bias$upr),
  RT_variability = sprintf("%s%.2f [%.2f, %.2f]",
                    ifelse(load_confidence$RT_variability$sig, "*", ""),
                    load_confidence$RT_variability$loadings,
                    load_confidence$RT_variability$lwr,
                    load_confidence$RT_variability$upr),
)  %>% arrange(assessment)
knitr::kable(loadings)
```

assessment	fixation_variability	attention_bias	RT_variability
ab_away_1	-0.17 [-0.27, -0.08]	*-0.64 [-0.72, -0.55]	0.20 [0.10, 0.30]
ab_toward_1	-0.42 [-0.49, -0.34]	0.86 [0.79, 0.90]	0.10 [0.04, 0.17]
final_gaze_bias_1	0.25 [0.14, 0.36]	*0.58 [0.44, 0.68]	-0.01 [-0.12, 0.10]
gaze_bias_1	0.24 [0.20, 0.29]	*0.93 [0.87, 0.98]	0.00 [-0.04, 0.04]
init_gaze_bias_1	0.08 [-0.04, 0.21]	*0.43 [0.28, 0.57]	-0.08 [-0.20, 0.03]
mean_dp_away_1	0.00 [-0.05, 0.06]	-0.11 [-0.18, -0.04]	*0.92 [0.89, 0.95]
mean_dp_toward_1	0.06 [0.01, 0.13]	0.12 [0.05, 0.20]	*0.86 [0.80, 0.90]
mean_gaze_away_1	*0.89 [0.85, 0.93]	-0.16 [-0.23, -0.09]	0.02 [-0.03, 0.07]
mean_gaze_toward_1	*0.97 [0.94, 0.99]	0.15 [0.11, 0.20]	-0.01 [-0.05, 0.03]
var_dp_bias_1	0.01 [0.00, 0.03]	-0.00 [-0.02, 0.01]	*1.00 [0.99, 1.00]
var_gaze_bias_1	*0.78 [0.71, 0.85]	0.10 [0.05, 0.15]	0.19 [0.13, 0.25]