

# FFA Rasch Modelling

AUTHOR

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## 1 Setup

```
library(easystats) # convinient stats
library(here) # path hell
library(eRm) # Rasch models
library(mirt) # more IRT
library(MASS) # stats
library(lordif) # DIF
library(tidyverse) # data wrangling
library(psych) # factor analysis
library(lavaan) # CFAs
library(semPlot) # SEM plots
```

### 1.1 Import FFA data

---

```
d_filename <- "Achtsamkeit_Daten_FFAEichung_rekodiert_2.sav"

d <- data_read(here("raw-data", d_filename))
```

### 1.2 Median split

---

```
d2 <-
  d %>%
  filter(Geschlecht != "divers") %>%
  mutate(Geschlecht = as.character(Geschlecht)) %>%
  mutate(PHQ_medsplit = ifelse(PHQ_Sum >= median(PHQ_Sum), 1, 0),
         Alter_medsplit = ifelse(Alter >= median(Alter), 1, 0))
```

Yes, only two cases of sex "divers".

### 1.3 Check

---

Can we drop "diverse" sex without losing much data?

```
d %>%
  count(Geschlecht)
```

```
  Geschlecht    n
1  männlich 495
2  weiblich 515
3    divers   2
```

## 2 Prepare data

### 2.1 Select FFA items

```
ffa_items <-
  d2 %>%
  dplyr::select(starts_with("FFA_"))
```

### 2.2 Recode

```
ffa_items2 <-
  ffa_items %>%
  mutate(across(.cols = everything(),
    .fns = ~ case_when(. == "fast nie" ~ 0,
                        . == "eher selten" ~ 1,
                        . == "relativ oft" ~ 2,
                        . == "fast immer" ~ 3)))
```

### 2.3 Check

```
ffa_items2 %>%
  describe_distribution()
```

Variable	Mean	SD	IQR	Range	Skewness	Kurtosis
n	n_Missing					

---

FFA_1	1.91   0.85   1   [0.00, 3.00]   -0.52   -0.24
1010	0
FFA_2	1.51   0.89   1   [0.00, 3.00]   -7.47e-03   -0.73
1010	0
FFA_3	1.42   0.86   1   [0.00, 3.00]   0.02   -0.66
1010	0
FFA_4	1.89   0.85   2   [0.00, 3.00]   -0.40   -0.48
1010	0
FFA_5	1.84   0.83   1   [0.00, 3.00]   -0.44   -0.28
1010	0
FFA_6	1.80   0.82   1   [0.00, 3.00]   -0.29   -0.43
1010	0
FFA_7	1.78   0.84   1   [0.00, 3.00]   -0.39   -0.36
1010	0
FFA_8	1.84   0.77   1   [0.00, 3.00]   -0.29   -0.27
1010	0
FFA_9	1.71   0.84   1   [0.00, 3.00]   -0.26   -0.47
1010	0
FFA_10	1.72   0.85   1   [0.00, 3.00]   -0.29   -0.49
1010	0
FFA_11	1.74   0.84   1   [0.00, 3.00]   -0.28   -0.47
1010	0
FFA_12	1.54   0.86   1   [0.00, 3.00]   -0.07   -0.65
1010	0
FFA_13_rek	1.67   0.90   1   [0.00, 3.00]   -0.15   -0.76
1010	0
FFA_14	1.60   0.84   1   [0.00, 3.00]   -0.14   -0.54
1010	0

## 2.4 FFA-13

```
ffa13_items <-
  ffa_items2 %>%
  dplyr::select(-FFA_13_rek)

dim(ffa13_items)
```

```
[1] 1010 13
```

## 3 IRT Models FFA13 - one factor model

## 3.1 Rating Scale Model (RSM)

```
ffa_rsm1 <- RSM(ffa_items2, se = FALSE)
ffa_rsm1_ppar <- person.parameter(ffa_rsm1)
```

This model does not run, throws error due to singularity in matrix.

## 3.2 Partial Credit Model (PCM)

### 3.2.1 Estimate parameters

#### 3.2.1.1 FFA-14: 14 items

```
ffa_pcm1 <- PCM(ffa_items2)
thresholds(ffa_pcm1)
```

Design Matrix Block 1:

	Location	Threshold 1	Threshold 2	Threshold 3
FFA_1	0.26067	-0.94317	-0.22598	1.95115
FFA_2	0.91626	-0.67573	0.88345	2.54106
FFA_3	1.12831	-0.57636	0.99342	2.96786
FFA_4	0.22817	-1.21454	0.03671	1.86234
FFA_5	0.36060	-1.02959	-0.07687	2.18827
FFA_6	0.34979	-1.37675	0.17527	2.25084
FFA_7	0.48002	-0.93762	0.05186	2.32582
FFA_8	0.22446	-1.71550	0.02947	2.35943
FFA_9	0.58029	-1.04322	0.30623	2.47786
FFA_10	0.58014	-0.92527	0.26003	2.40568
FFA_11	0.50785	-1.09032	0.25214	2.36172
FFA_12	0.88470	-0.77655	0.76261	2.66804
FFA_13_rek	0.62526	-0.85574	0.59710	2.13443
FFA_14	0.76323	-0.99528	0.59661	2.68836

```
ffa_pcm1_ppar <- person.parameter(ffa_pcm1)
ffa_pcm1_ppar
```

## Person Parameters:

Raw Score	Estimate	Std.Error
3	-2.47563019	0.6110641
4	-2.14746247	0.5393721
5	-1.88288301	0.4918666
6	-1.65803307	0.4580168
7	-1.46010308	0.4327927
8	-1.28138631	0.4134650
9	-1.11680549	0.3984023
10	-0.96292147	0.3865766
11	-0.81719887	0.3772888
12	-0.67766802	0.3700483
13	-0.54286015	0.3645077
14	-0.41157499	0.3604056
15	-0.28277307	0.3575391
16	-0.15562456	0.3557542
17	-0.02941778	0.3549217
18	0.09649900	0.3549390
19	0.22270913	0.3557148
20	0.34973478	0.3571744
21	0.47802889	0.3592494
22	0.60799865	0.3618793
23	0.74004711	0.3650126
24	0.87456811	0.3686113
25	1.01192106	0.3726488
26	1.15244051	0.3771211
27	1.29648521	0.3820526
28	1.44448274	0.3875043
29	1.59695652	0.3935906
30	1.75455113	0.4004877
31	1.91808584	0.4084536
32	2.08866648	0.4178543
33	2.26786312	0.4292056
34	2.45792067	0.4432464
35	2.66204174	0.4610582
36	2.88497992	0.4843112
37	3.13422277	0.5157722
38	3.42238345	0.5604822
39	3.77318878	0.6289827
40	4.23992101	0.7486760
41	4.99249392	1.0290806
42	5.81436949	NA

```
ffa_pcm1_itemfit <- eRm::itemfit(ffa_pcm1_ppar)
ffa_pcm1_itemfit
```

#### Itemfit Statistics:

	Chisq	df	p-value	Outfit MSQ	Infit MSQ	Outfit t	Infit
FFA_1	1012.904	1002	0.398	1.010	0.979	0.231	
-0.458	0.522						
FFA_2	1074.782	1002	0.054	1.072	1.051	1.684	
1.226	0.492						
FFA_3	1066.561	1002	0.077	1.063	1.064	1.504	
1.535	0.470						
FFA_4	849.198	1002	1.000	0.847	0.850	-3.647	
-3.707	0.614						
FFA_5	758.503	1002	1.000	0.756	0.767	-5.965	
-5.809	0.667						
FFA_6	784.800	1002	1.000	0.782	0.798	-5.439	
-5.081	0.646						
FFA_7	746.182	1002	1.000	0.744	0.762	-6.368	
-6.000	0.677						
FFA_8	959.878	1002	0.826	0.957	0.952	-0.985	
-1.113	0.517						
FFA_9	796.610	1002	1.000	0.794	0.799	-5.140	
-5.073	0.648						
FFA_10	770.208	1002	1.000	0.768	0.777	-5.836	
-5.705	0.665						
FFA_11	749.025	1002	1.000	0.747	0.756	-6.436	
-6.277	0.676						
FFA_12	795.992	1002	1.000	0.794	0.799	-5.295	
-5.210	0.650						
FFA_13_rek	2651.416	1002	0.000	2.643	1.855	27.010	
16.750	-0.021						
FFA_14	979.859	1002	0.686	0.977	0.951	-0.536	
-1.184	0.538						

This model shows a bad fit.

### 3.2.1.2 FFA-13: 13 item

```
ffa_pcm2 <- PCM(ffa13_items)
ffa_pcm2_ppar <- person.parameter(ffa_pcm2)
```

```
ffa_pcm2_itemfit2 <- eRm::itemfit(ffa_pcm2_ppar)
ffa_pcm2_itemfit2
```

### Itemfit Statistics:

	Chisq	df	p-value	Outfit MSQ	Infit MSQ	Outfit t	Infit t
Discrim							
FFA_1	1128.015	985	0.001	1.144	1.062	3.009	1.371
0.492							
FFA_2	1147.431	985	0.000	1.164	1.111	3.635	2.568
0.472							
FFA_3	1134.305	985	0.001	1.150	1.129	3.355	2.973
0.446							
FFA_4	952.263	985	0.768	0.966	0.935	-0.761	-1.540
0.579							
FFA_5	805.340	985	1.000	0.817	0.822	-4.313	-4.279
0.644							
FFA_6	837.713	985	1.000	0.850	0.859	-3.613	-3.399
0.619							
FFA_7	776.805	985	1.000	0.788	0.800	-5.089	-4.886
0.662							
FFA_8	1041.978	985	0.101	1.057	1.030	1.280	0.687
0.482							
FFA_9	868.430	985	0.997	0.881	0.878	-2.820	-2.931
0.611							
FFA_10	804.569	985	1.000	0.816	0.829	-4.447	-4.193
0.643							
FFA_11	822.820	985	1.000	0.835	0.833	-3.987	-4.085
0.638							
FFA_12	838.186	985	1.000	0.850	0.856	-3.665	-3.579
0.625							
FFA_14	1042.183	985	0.100	1.057	1.019	1.309	0.457
0.509							

## 3.2.2 Overall Goodness of Fit

```
#gofIRT(ffa_pcm2_ppar) # not implemented for polytomuous models yet
#item_info(ffa_pcm2)
```

## 3.2.3 Andersen test

Significant results indicate that the exercise parameter differ significantly between the two groups.

```
LRtest(ffa_pcm2) # nicht so gut
```

Andersen LR-test:  
LR-value: 168.57  
Chi-square df: 35  
p-value: 0

```
LRtest(ffa_pcm2, d2$Evang) # ok
```

Andersen LR-test:  
LR-value: 57.32  
Chi-square df: 38  
p-value: 0.023

```
LRtest(ffa_pcm2, d2$Theorie) # nicht so gut
```

Andersen LR-test:  
LR-value: 119.295  
Chi-square df: 38  
p-value: 0

```
LRtest(ffa_pcm2, d2$PHQ_medsplit) # nicht so gut
```

Andersen LR-test:  
LR-value: 253.068  
Chi-square df: 38  
p-value: 0

### 3.2.4 Wald Test

```
Waldtest(ffa_pcm2)
```

Wald test on item level (z-values):



	z-statistic	p-value
beta FFA_1.c1	4.506	0.000
beta FFA_1.c2	3.313	0.001
beta FFA_1.c3	1.406	0.160
beta FFA_2.c1	1.703	0.089
beta FFA_2.c2	-0.342	0.732
beta FFA_2.c3	0.099	0.921
beta FFA_3.c1	3.435	0.001
beta FFA_3.c2	2.098	0.036
beta FFA_3.c3	0.842	0.400
beta FFA_4.c1	-0.097	0.922
beta FFA_4.c2	-0.894	0.371
beta FFA_4.c3	-1.318	0.187
beta FFA_5.c1	0.021	0.984
beta FFA_5.c2	-1.239	0.215
beta FFA_5.c3	-2.135	0.033
beta FFA_7.c1	-0.063	0.950
beta FFA_7.c2	-1.739	0.082
beta FFA_7.c3	-2.886	0.004
beta FFA_8.c1	4.104	0.000
beta FFA_8.c2	2.937	0.003
beta FFA_8.c3	2.192	0.028
beta FFA_9.c1	1.163	0.245
beta FFA_9.c2	-0.938	0.348
beta FFA_9.c3	-1.972	0.049
beta FFA_10.c1	2.395	0.017
beta FFA_10.c2	0.048	0.962
beta FFA_10.c3	-0.583	0.560
beta FFA_11.c1	1.771	0.077
beta FFA_11.c2	-0.710	0.478
beta FFA_11.c3	-1.462	0.144
beta FFA_12.c1	-1.497	0.134
beta FFA_12.c2	-3.005	0.003
beta FFA_12.c3	-3.033	0.002
beta FFA_14.c1	2.537	0.011
beta FFA_14.c2	1.072	0.284
beta FFA_14.c3	0.952	0.341

```
Waldtest(ffa_pcm2, d2$PHQ_medsplit)
```

Wald test on item level (z-values):

	z-statistic	p-value
beta FFA_1.c1	0.280	0.779
beta FFA_1.c2	1.678	0.093
beta FFA_1.c3	2.732	0.006
beta FFA_2.c1	-4.512	0.000
beta FFA_2.c2	-5.186	0.000
beta FFA_2.c3	-6.045	0.000
beta FFA_3.c1	-5.622	0.000
beta FFA_3.c2	-7.385	0.000
beta FFA_3.c3	-6.354	0.000
beta FFA_4.c1	0.652	0.514
beta FFA_4.c2	2.637	0.008
beta FFA_4.c3	3.856	0.000
beta FFA_5.c1	-1.845	0.065
beta FFA_5.c2	-1.191	0.234
beta FFA_5.c3	-1.043	0.297
beta FFA_6.c1	0.561	0.575
beta FFA_6.c2	1.790	0.074
beta FFA_6.c3	1.669	0.095
beta FFA_7.c1	-2.465	0.014
beta FFA_7.c2	-1.011	0.312
beta FFA_7.c3	0.112	0.911
beta FFA_8.c1	0.129	0.897
beta FFA_8.c2	-0.393	0.694
beta FFA_8.c3	0.431	0.667
beta FFA_9.c1	0.605	0.545
beta FFA_9.c2	3.150	0.002
beta FFA_9.c3	4.208	0.000
beta FFA_10.c1	-2.569	0.010
beta FFA_10.c2	-1.876	0.061
beta FFA_10.c3	-1.783	0.075
beta FFA_11.c1	0.270	0.787
beta FFA_11.c2	2.763	0.006
beta FFA_11.c3	3.017	0.003
beta FFA_12.c1	1.119	0.263
beta FFA_12.c2	2.903	0.004
beta FFA_12.c3	2.149	0.032
beta FFA_14.c1	1.156	0.248
beta FFA_14.c2	2.015	0.044
beta FFA_14.c3	0.817	0.414

### 3.2.5 MLoef Test

```
MLoef(ffa_pcm2) # good
```

Martin-Loef-Test (split criterion: median)

LR-value: 378.543

Chi-square df: 377

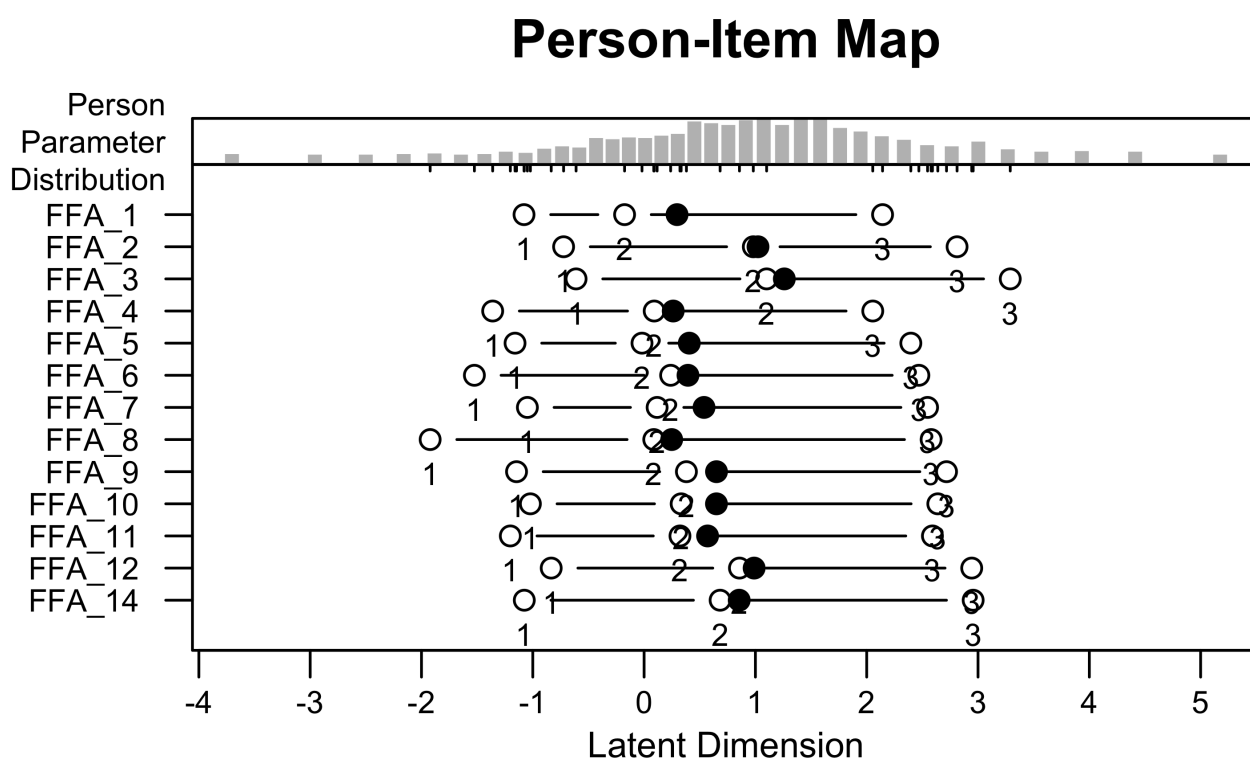
p-value: 0.468

## 3.2.6 Item information

```
plotINFO(ffa_pcm2, legpos = FALSE)
```

Error in plot.new(): figure margins too large

```
plotPImap(ffa_pcm2)
```



## 4 Two factor model

### 4.1 Devise factors

Items were assigned according to Sauer et al., 2013.

```
presence_factor <- c(1, 2, 3, 5, 7)
acceptance_factor <- c(4, 6, 8, 9, 10, 11, 12, 14)
```

```
ffa13_pres <-
  ffa_items2 %>%
  dplyr::select(any_of(presence_factor))

ffa13_acc <-
  ffa_items2 %>%
  dplyr::select(any_of(acceptance_factor))
```

## 4.2 Check distributions

```
ffa13_pres %>%
  describe_distribution()
```

Variable	Mean	SD	IQR	Range	Skewness	Kurtosis	n	n_Missing
----------	------	----	-----	-------	----------	----------	---	-----------

FFA_1	1.91	0.85	1	[0.00, 3.00]	-0.52	-0.24	1010	0
FFA_2	1.51	0.89	1	[0.00, 3.00]	-7.47e-03	-0.73	1010	0
FFA_3	1.42	0.86	1	[0.00, 3.00]	0.02	-0.66	1010	0
FFA_5	1.84	0.83	1	[0.00, 3.00]	-0.44	-0.28	1010	0
FFA_7	1.78	0.84	1	[0.00, 3.00]	-0.39	-0.36	1010	0

```
ffa13_acc %>%
  describe_distribution()
```

Variable	Mean	SD	IQR	Range	Skewness	Kurtosis	n	n_Missing
----------	------	----	-----	-------	----------	----------	---	-----------

FFA_4	1.89	0.85	2	[0.00, 3.00]	-0.40	-0.48
1010	0					
FFA_6	1.80	0.82	1	[0.00, 3.00]	-0.29	-0.43
1010	0					
FFA_8	1.84	0.77	1	[0.00, 3.00]	-0.29	-0.27
1010	0					
FFA_9	1.71	0.84	1	[0.00, 3.00]	-0.26	-0.47
1010	0					
FFA_10	1.72	0.85	1	[0.00, 3.00]	-0.29	-0.49
1010	0					
FFA_11	1.74	0.84	1	[0.00, 3.00]	-0.28	-0.47
1010	0					
FFA_12	1.54	0.86	1	[0.00, 3.00]	-0.07	-0.65
1010	0					
FFA_14	1.60	0.84	1	[0.00, 3.00]	-0.14	-0.54
1010	0					

## 4.3 Any categories not chosen?

Let's check if any category was not chosen at all, which may cause the model to fail [according to this source](#).

```
ffa13_acc %>%
  pivot_longer(everything(), names_to = "item", values_to = "category")
  count(item, category, sort = TRUE)
```

```
# A tibble: 32 × 3
  item    category     n
  <chr>      <dbl> <int>
1 FFA_8          2   514
2 FFA_6          2   477
3 FFA_11         2   469
4 FFA_9          2   469
5 FFA_10         2   467
6 FFA_4          2   453
7 FFA_14         2   436
8 FFA_12         2   401
9 FFA_12         1   357
10 FFA_14         1   341
# ... with 22 more rows
```

However, there appear to be no category with zero count.

## 5 RSM

### 5.1 Presence

#### 5.1.1 Parameter estimation

```
ffa_rsm1_pres <- RSM(ffa13_pres, se = TRUE)
ffa_rsm1_pres
```

Results of RSM estimation:

Call: RSM(X = ffa13\_pres, se = TRUE)

Conditional log-likelihood: -3195.759

Number of iterations: 18

Number of parameters: 6

Item (Category) Difficulty Parameters (eta):

	FFA_2	FFA_3	FFA_5	FFA_7	Cat 2
Cat 3					
Estimate	0.39599666	0.58536426	-0.32090754	-0.18635947	1.41513967
	5.0277889				
Std.Err	0.04180639	0.04274221	0.04263715	0.04196558	0.08641274
	0.1740857				

```
ffa_rsm1_pres_ppar <- person.parameter(ffa_rsm1_pres)
```

#### 5.1.2 Itemfit

```
eRm::itemfit(ffa_rsm1_pres_ppar)
```

Itemfit Statistics:

	Chisq	df	p-value	Outfit MSQ	Infit MSQ	Outfit t	Infit t
Discrim							
FFA_1	883.502	971	0.979	0.909	0.927	-2.093	-1.697

0.477

FFA_2	819.184	971	1.000	0.843	0.823	-3.866	-4.429
-------	---------	-----	-------	-------	-------	--------	--------

0.538

FFA_3	847.283	971	0.998	0.872	0.859	-3.123	-3.500
-------	---------	-----	-------	-------	-------	--------	--------

0.472

FFA_5	771.695	971	1.000	0.794	0.793	-5.018	-5.082
-------	---------	-----	-------	-------	-------	--------	--------

0.550

FFA_7	735.241	971	1.000	0.756	0.751	-6.071	-6.260
-------	---------	-----	-------	-------	-------	--------	--------

0.589

Looks good.

## 5.1.3 Andersen test

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
LRtest(ffa_rsm1_pres) # sign.
```

Andersen LR-test:

LR-value: 25.923

Chi-square df: 6

p-value: 0

```
LRtest(ffa_rsm1_pres, d2$Evang) # sign
```

Andersen LR-test:

LR-value: 15.57

Chi-square df: 6

p-value: 0.016

```
LRtest(ffa_rsm1_pres, d2$Theorie) # sign
```

Andersen LR-test:

LR-value: 42.911

Chi-square df: 6

p-value: 0

```
#PHQ_medsplit <- ifelse(d$PHQ_Sum >= median(d$PHQ_Sum), "+", "-")
```

```
LRtest(ffa_rsm1_pres, d2$PHQ_medsplit) # sign
```

Andersen LR-test:

LR-value: 113.556

Chi-square df: 6

p-value: 0

## 5.1.4 Wald Test

The Wald Tests computes the difference in item difficulty normalized to their SE between two groups.

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
Waldtest(ffa_rsm1_pres) # sign mostly
```

Wald test on item level (z-values):

	z-statistic	p-value
beta FFA_1.c1	-0.507	0.612
beta FFA_1.c2	-4.207	0.000
beta FFA_1.c3	-4.032	0.000
beta FFA_2.c1	-1.989	0.047
beta FFA_2.c2	-4.861	0.000
beta FFA_2.c3	-4.421	0.000
beta FFA_3.c1	0.879	0.379
beta FFA_3.c2	-3.266	0.001
beta FFA_3.c3	-3.070	0.002
beta FFA_5.c1	0.538	0.591
beta FFA_5.c2	-3.687	0.000
beta FFA_5.c3	-3.551	0.000
beta FFA_7.c1	1.061	0.289
beta FFA_7.c2	-3.432	0.001
beta FFA_7.c3	-3.306	0.001

```
Waldtest(ffa_rsm1_pres, d2$PHQ_medsplit) # signif mostly
```

Wald test on item level (z-values):



	z-statistic	p-value
beta FFA_1.c1	5.445	0.000
beta FFA_1.c2	6.955	0.000
beta FFA_1.c3	6.557	0.000
beta FFA_2.c1	-4.458	0.000
beta FFA_2.c2	-0.527	0.598
beta FFA_2.c3	-0.139	0.889
beta FFA_3.c1	-5.848	0.000
beta FFA_3.c2	-1.506	0.132
beta FFA_3.c3	-0.951	0.342
beta FFA_5.c1	1.324	0.185
beta FFA_5.c2	3.671	0.000
beta FFA_5.c3	3.509	0.000
beta FFA_7.c1	3.341	0.001
beta FFA_7.c2	5.111	0.000
beta FFA_7.c3	4.704	0.000

## 5.1.5 MLOEF Test

The M Loef tests checks whether the person parameter differ between items. According to the assumptions of the Rasch models, we expect invariance, i.e., there should be not subset of items for which the person parameters differ from the rest of the items.

```
MLoef(ffa_rsm1_pres) # signif
```

Martin-Loef-Test (split criterion: median)

LR-value: 124.152

Chi-square df: 53

p-value: 0

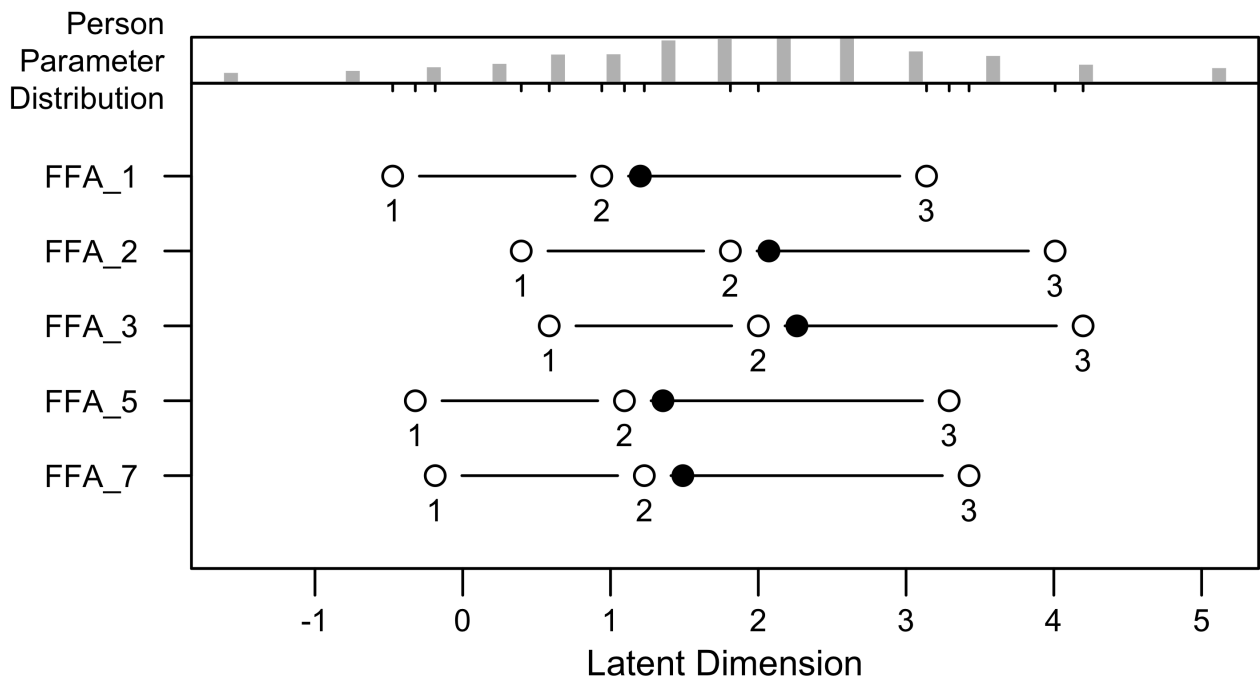
## 5.1.6 Item information

```
plotINFO(ffa_rsm1_pres, legpos = FALSE)
```

Error in plot.new(): figure margins too large

```
plotPimap(ffa_rsm1_pres)
```

## Person-Item Map



## 5.2 Acceptance

### 5.2.1 Parameter estimation

This does NOT Run:

```
ffa_rsm1_acc <- RSM(ffa13_acc, se = TRUE)
ffa_rsm1_acc
ffa_rsm1_acc_ppar <- person.parameter(ffa_rsm1_acc)
```

Oh no: NaNs have been produced. There must be some edge cases in the data.

### 5.2.2 Itemfit

```
eRm::itemfit(ffa_rsm1_acc_ppar)
```

### 5.2.3 Itemfit

```
eRm::itemfit(ffa_rsm1_pres_ppar)
```

## Itemfit Statistics:

	Chisq	df	p-value	Outfit MSQ	Infit MSQ	Outfit t	Infit t
Discrim							
FFA_1	883.502	971	0.979	0.909	0.927	-2.093	-1.697
0.477							
FFA_2	819.184	971	1.000	0.843	0.823	-3.866	-4.429
0.538							
FFA_3	847.283	971	0.998	0.872	0.859	-3.123	-3.500
0.472							
FFA_5	771.695	971	1.000	0.794	0.793	-5.018	-5.082
0.550							
FFA_7	735.241	971	1.000	0.756	0.751	-6.071	-6.260
0.589							

## 5.2.4 Andersen test

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
LRtest(ffa_rsm1_acc) # does not run
```

```
Error in LRtest(ffa_rsm1_acc): object 'ffa_rsm1_acc' not found
```

```
LRtest(ffa_rsm1_acc, d2$Evang) # sign
```

```
Error in LRtest(ffa_rsm1_acc, d2$Evang): object 'ffa_rsm1_acc' not found
```

```
LRtest(ffa_rsm1_acc, d2$Theorie) # sign
```

```
Error in LRtest(ffa_rsm1_acc, d2$Theorie): object 'ffa_rsm1_acc' not found
```

```
#PHQ_medsplit <- ifelse(d$PHQ_Sum >= median(d$PHQ_Sum), "+", "-")
LRtest(ffa_rsm1_acc, d2$PHQ_medsplit) # sign
```

```
Error in LRtest(ffa_rsm1_acc, d2$PHQ_medsplit): object 'ffa_rsm1_acc' not found
```

## 5.2.5 Wald Test

The Wald Tests computes the difference in item difficulty normalized to their SE between two groups.

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

This function yields error (singular matrix).

```
#Waldtest(ffa_rsm1_acc) # sign mostly  
#Waldtest(ffa_rsm1_acc, d2$PHQ_medsplit) # signif mostly
```

## 5.2.6 MLOEF Test

The M Loef tests checks whether the person parameter differ between items. According to the assumptions of the Rasch models, we expect invariance, i.e., there should be not subset of items for which the person parameters differ from the rest of the items.

```
MLoef(ffa_rsm1_acc) # signif
```

Error in MLoef(ffa\_rsm1\_acc): object 'ffa\_rsm1\_acc' not found

## 5.2.7 Item information

```
plotINFO(ffa_rsm1_acc, legpos = FALSE)
```

Error in get\_item\_cats(X = ermobject\$X, nitems = dim(ermobject\$X)[2], : object 'ffa\_rsm1\_acc' not found

```
plotPimap(ffa_rsm1_acc)
```

Error in plotPimap(ffa\_rsm1\_acc): object 'ffa\_rsm1\_acc' not found

## 5.3 Conclusion

The RSM is not appropriate for the data for some reason that is not entirely clear.

## 6 PCM

## 6.1 Presence

### 6.1.1 Parameter estimation

```
ffa_pcm1_pres <- PCM(ffa13_pres, se = TRUE)
ffa_pcm1_pres
```

Results of PCM estimation:

Call: PCM(X = ffa13\_pres, se = TRUE)

Conditional log-likelihood: -3183.913

Number of iterations: 31

Number of parameters: 14

Item (Category) Difficulty Parameters (eta):

	FFA_1.c2	FFA_1.c3	FFA_2.c1	FFA_2.c2	FFA_2.c3
FFA_3.c1					
Estimate	-1.4679274	0.5501084	-0.8282963	0.04465034	2.7220750
	-0.7154672				
Std.Err	0.1357334	0.1471584	0.1050176	0.11326886	0.1570351
	0.1001023				
	FFA_3.c2	FFA_3.c3	FFA_5.c1	FFA_5.c2	FFA_5.c3
FFA_7.c1					
Estimate	0.2742468	3.4297143	-1.2716971	-1.3931592	0.8767761
	-1.1587477				
Std.Err	0.1108744	0.1704769	0.1424045	0.1338912	0.1498455
	0.1334806				
	FFA_7.c2	FFA_7.c3			
Estimate	-1.1452605	1.2737425			
Std.Err	0.1275336	0.1494924			

```
ffa_pcm1_pres_ppar <- person.parameter(ffa_pcm1_pres)
```

### 6.1.2 Itemfit

```
eRm::itemfit(ffa_pcm1_pres_ppar)
```

## Itemfit Statistics:

	Chisq	df	p-value	Outfit MSQ	Infit MSQ	Outfit t	Infit t
Discrim							
FFA_1	856.206	971	0.997	0.881	0.890	-2.719	-2.540
	0.477						
FFA_2	801.639	971	1.000	0.825	0.806	-4.375	-4.907
	0.538						
FFA_3	874.078	971	0.988	0.899	0.894	-2.444	-2.585
	0.472						
FFA_5	773.795	971	1.000	0.796	0.795	-4.903	-4.965
	0.550						
FFA_7	738.222	971	1.000	0.759	0.755	-5.917	-6.092
	0.589						

Quite good.

### 6.1.3 Andersen test

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
LRtest(ffa_pcm1_pres) # sign.
```

Andersen LR-test:

LR-value: 34.352

Chi-square df: 14

p-value: 0.002

```
LRtest(ffa_pcm1_pres, d2$Evang) # NOT sign
```

Andersen LR-test:

LR-value: 20.603

Chi-square df: 14

p-value: 0.112

```
LRtest(ffa_pcm1_pres, d2$Theorie) # sign
```

Andersen LR-test:

LR-value: 54.516

Chi-square df: 14  
p-value: 0

```
#PHQ_medsplit <- ifelse(d$PHQ_Sum >= median(d$PHQ_Sum), "+", "-")
LRtest(ffa_pcm1_pres, d2$PHQ_medsplit) # sign
```

Andersen LR-test:  
LR-value: 123.54  
Chi-square df: 14  
p-value: 0

## 6.1.4 Wald Test

The Wald Tests computes the difference in item difficulty normalized to their SE between two groups.

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
Waldtest(ffa_pcm1_pres) # mostly NOT signif
```

Wald test on item level (z-values):

	z-statistic	p-value
beta FFA_1.c1	3.305	0.001
beta FFA_1.c2	1.858	0.063
beta FFA_1.c3	0.835	0.404
beta FFA_2.c1	1.971	0.049
beta FFA_2.c2	-0.530	0.596
beta FFA_2.c3	-1.313	0.189
beta FFA_3.c1	0.471	0.638
beta FFA_3.c2	-1.470	0.141
beta FFA_3.c3	-1.077	0.282
beta FFA_5.c1	0.490	0.624
beta FFA_5.c2	-0.395	0.693
beta FFA_5.c3	-0.988	0.323
beta FFA_7.c1	0.105	0.917
beta FFA_7.c2	-0.864	0.388
beta FFA_7.c3	-1.239	0.215

```
Waldtest(ffa_pcm1_pres, d2$PHQ_medsplit) # mixed picture as to signi
```

Wald test on item level (z-values):

	z-statistic	p-value
beta FFA_1.c1	1.193	0.233
beta FFA_1.c2	4.028	0.000
beta FFA_1.c3	6.154	0.000
beta FFA_2.c1	-2.984	0.003
beta FFA_2.c2	-2.408	0.016
beta FFA_2.c3	-2.998	0.003
beta FFA_3.c1	-4.059	0.000
beta FFA_3.c2	-4.572	0.000
beta FFA_3.c3	-3.494	0.000
beta FFA_5.c1	-0.800	0.424
beta FFA_5.c2	1.207	0.227
beta FFA_5.c3	2.082	0.037
beta FFA_7.c1	-1.333	0.182
beta FFA_7.c2	1.568	0.117
beta FFA_7.c3	3.391	0.001

## 6.1.5 MLOEF Test

The M Loef tests checks whether the person parameter differ between items. According to the assumptions of the Rasch models, we expect invariance, i.e., there should be not subset of items for which the person parameters differ from the rest of the items.

```
MLoef(ffa_pcm1_pres) # signif
```

```
Martin-Loef-Test (split criterion: median)
LR-value: 100.46
Chi-square df: 53
p-value: 0
```

## 6.1.6 Item information

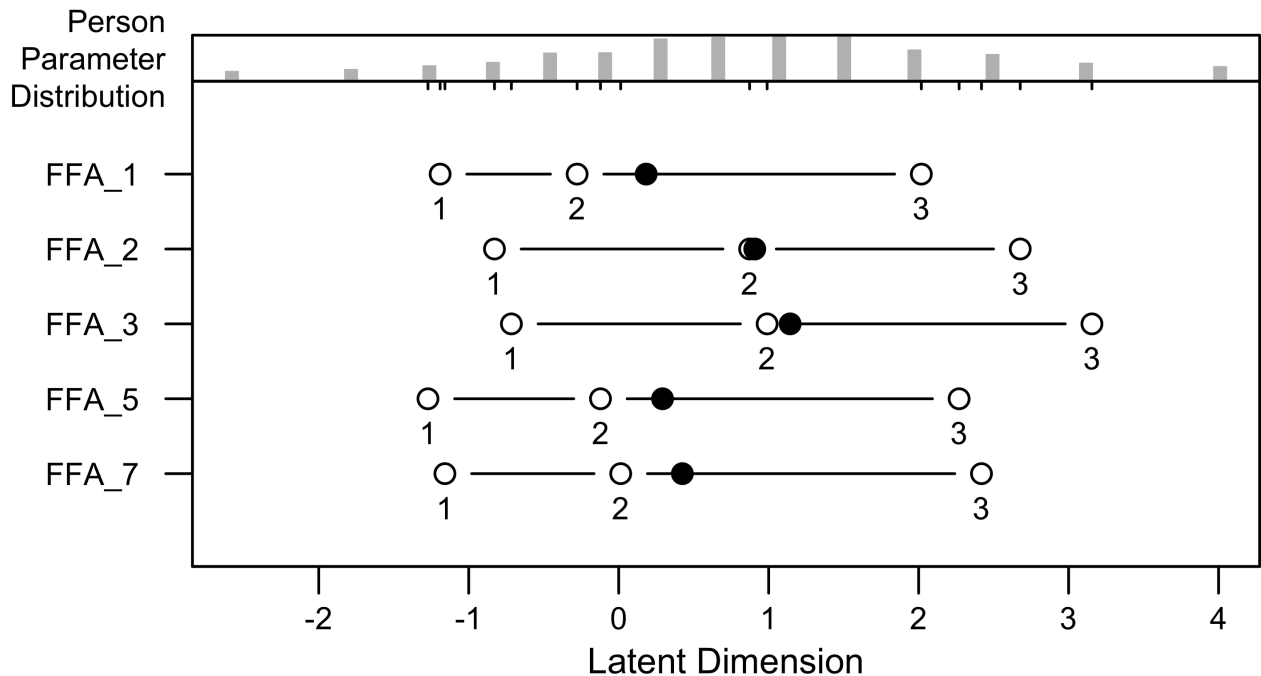
```
plotINFO(ffa_pcm1_pres, legpos = FALSE)
```



Error in plot.new(): figure margins too large

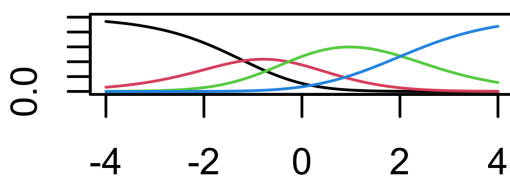
```
plotPImap(ffa_pcm1_pres)
plotICC(ffa_pcm1_pres, mplot=TRUE, legpos=FALSE, ask=FALSE)
```

## Person-Item Map



Probability to Solve

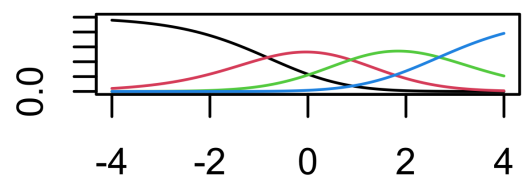
### ICC plot for item FFA\_1



Latent Dimension

Probability to Solve

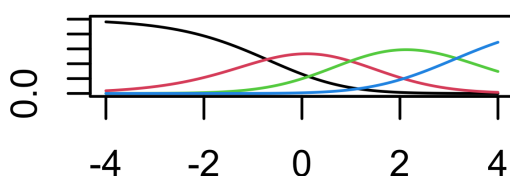
### ICC plot for item FFA\_2



Latent Dimension

Probability to Solve

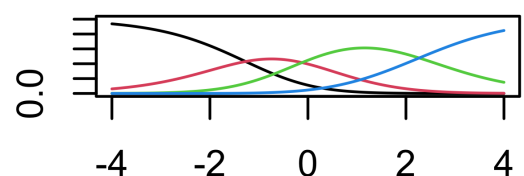
### ICC plot for item FFA\_3



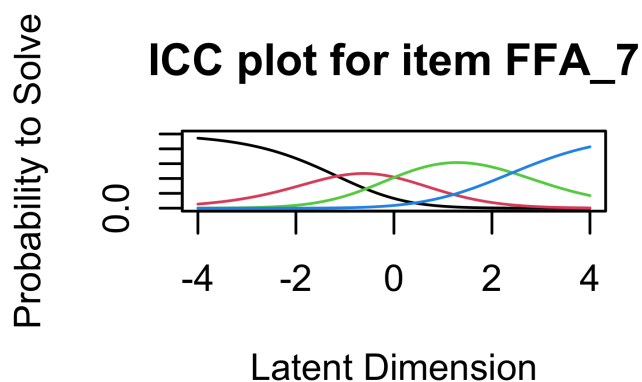
Latent Dimension

Probability to Solve

### ICC plot for item FFA\_5



Latent Dimension



## 6.2 Acceptance

### 6.2.1 Parameter estimation

```
ffa_pcm1_acc <- PCM(ffa13_acc, se = TRUE)
ffa_pcm1_acc
```

Results of PCM estimation:

Call: PCM(X = ffa13\_acc, se = TRUE)

Conditional log-likelihood: -5665.854

Number of iterations: 27

Number of parameters: 23

Item (Category) Difficulty Parameters (eta):

	FFA_4.c2	FFA_4.c3	FFA_6.c1	FFA_6.c2	FFA_6.c3
FFA_8.c1					
Estimate	-1.198001	1.0485305	-1.5537148	-1.208498	1.4719554
	-1.9861856				
Std.Err	0.151804	0.1662774	0.1553209	0.153429	0.1730271

0.1832482

```

          FFA_8.c2  FFA_8.c3   FFA_9.c1   FFA_9.c2   FFA_9.c3
FFA_10.c1
Estimate -1.7975028 0.9951131 -1.1475755 -0.6528500 2.2922089
-1.0194943
Std.Err   0.1774485 0.1913627 0.1339019 0.1355878 0.1659322
0.1308545

```

```

          FFA_10.c2 FFA_10.c3  FFA_11.c1  FFA_11.c2 FFA_11.c3
FFA_12.c1
Estimate -0.5725264 2.2895048 -1.2088360 -0.7746536 2.0360393
-0.8061815
Std.Err   0.1326501 0.1625221 0.1379859 0.1387522 0.1654349
0.1132583

```

```

          FFA_12.c2 FFA_12.c3  FFA_14.c1  FFA_14.c2 FFA_14.c3
Estimate 0.178661 3.376419 -1.0632220 -0.2573247 2.9479657
Std.Err 0.122176 0.167022 0.1238444 0.1292577 0.1692504

```

```
ffa_pcm1_acc_ppar <- person.parameter(ffa_pcm1_acc)
```

## 6.2.2 Itemfit

```
eRm::itemfit(ffa_pcm1_acc_ppar)
```

### Itemfit Statistics:

	Chisq	df	p-value	Outfit MSQ	Infit MSQ	Outfit t	Infit t
Discrim							
FFA_4	935.975	977	0.823	0.957	0.916	-0.941	-1.974
0.569							
FFA_6	820.706	977	1.000	0.839	0.837	-3.827	-3.943
0.614							
FFA_8	1051.808	977	0.048	1.075	1.081	1.669	1.795
0.426							
FFA_9	767.624	977	1.000	0.785	0.779	-5.238	-5.474
0.655							
FFA_10	855.842	977	0.998	0.875	0.863	-2.915	-3.284
0.601							
FFA_11	780.714	977	1.000	0.798	0.791	-4.876	-5.142
0.647							
FFA_12	814.717	977	1.000	0.833	0.826	-4.075	-4.305
0.627							

FFA\_14 1029.331 977 0.119 1.052 1.029 1.199 0.682  
0.483

Quite good.

### 6.2.3 Andersen test

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
LRtest(ffa_pcm1_acc) # signif
```

Andersen LR-test:

LR-value: 112.123

Chi-square df: 20

p-value: 0

```
LRtest(ffa_pcm1_acc, d2$Evang) # NOT sign
```

Andersen LR-test:

LR-value: 31.755

Chi-square df: 23

p-value: 0.105

```
LRtest(ffa_pcm1_acc, d2$Theorie) # sign
```

Andersen LR-test:

LR-value: 52.22

Chi-square df: 23

p-value: 0

```
#PHQ_medsplit <- ifelse(d$PHQ_Sum >= median(d$PHQ_Sum), "+", "-")
LRtest(ffa_pcm1_acc, d2$PHQ_medsplit) # sign
```

Andersen LR-test:

LR-value: 71.234

Chi-square df: 23

p-value: 0

## 6.2.4 Wald Test

The Wald Tests computes the difference in item difficulty normalized to their SE between two groups.

A significant results indicates that the item parameters differ between groups, which indicates a violation of the Rasch model's assumption.

```
Waldtest(ffa_pcm1_acc) # mostly not signif
```

Wald test on item level (z-values):

	z-statistic	p-value
beta FFA_4.c1	-0.321	0.748
beta FFA_4.c2	-1.191	0.234
beta FFA_4.c3	-1.436	0.151
beta FFA_8.c1	4.036	0.000
beta FFA_8.c2	2.920	0.004
beta FFA_8.c3	3.021	0.003
beta FFA_9.c1	1.289	0.197
beta FFA_9.c2	-0.901	0.367
beta FFA_9.c3	-2.024	0.043
beta FFA_10.c1	3.723	0.000
beta FFA_10.c2	0.964	0.335
beta FFA_10.c3	0.330	0.742
beta FFA_11.c1	0.880	0.379
beta FFA_11.c2	-1.155	0.248
beta FFA_11.c3	-1.388	0.165
beta FFA_12.c1	-1.429	0.153
beta FFA_12.c2	-3.112	0.002
beta FFA_12.c3	-2.438	0.015
beta FFA_14.c1	2.509	0.012
beta FFA_14.c2	0.706	0.480
beta FFA_14.c3	1.481	0.139

```
Waldtest(ffa_pcm1_acc, d2$PHQ_medsplit) # NOT signif
```

Wald test on item level (z-values):

z-statistic	p-value
-------------	---------

beta FFA_4.c1	0.269	0.788
beta FFA_4.c2	1.564	0.118
beta FFA_4.c3	2.220	0.026
beta FFA_6.c1	0.120	0.904
beta FFA_6.c2	0.687	0.492
beta FFA_6.c3	-0.026	0.979
beta FFA_8.c1	-0.225	0.822
beta FFA_8.c2	-1.323	0.186
beta FFA_8.c3	-1.100	0.271
beta FFA_9.c1	0.027	0.978
beta FFA_9.c2	1.841	0.066
beta FFA_9.c3	2.322	0.020
beta FFA_10.c1	-3.520	0.000
beta FFA_10.c2	-3.552	0.000
beta FFA_10.c3	-3.887	0.000
beta FFA_11.c1	-0.305	0.761
beta FFA_11.c2	1.453	0.146
beta FFA_11.c3	1.122	0.262
beta FFA_12.c1	0.279	0.780
beta FFA_12.c2	1.315	0.189
beta FFA_12.c3	0.042	0.967
beta FFA_14.c1	0.408	0.683
beta FFA_14.c2	0.551	0.582
beta FFA_14.c3	-1.188	0.235

## 6.2.5 MLOEF Test

The M Loef tests checks whether the person parameter differ between items. According to the assumptions of the Rasch models, we expect invariance, i.e., there should be not subset of items for which the person parameters differ from the rest of the items.

```
MLoef(ffa_pcm1_acc) # NOT signif
```

Martin-Loef-Test (split criterion: median)

LR-value: 152.265

Chi-square df: 143

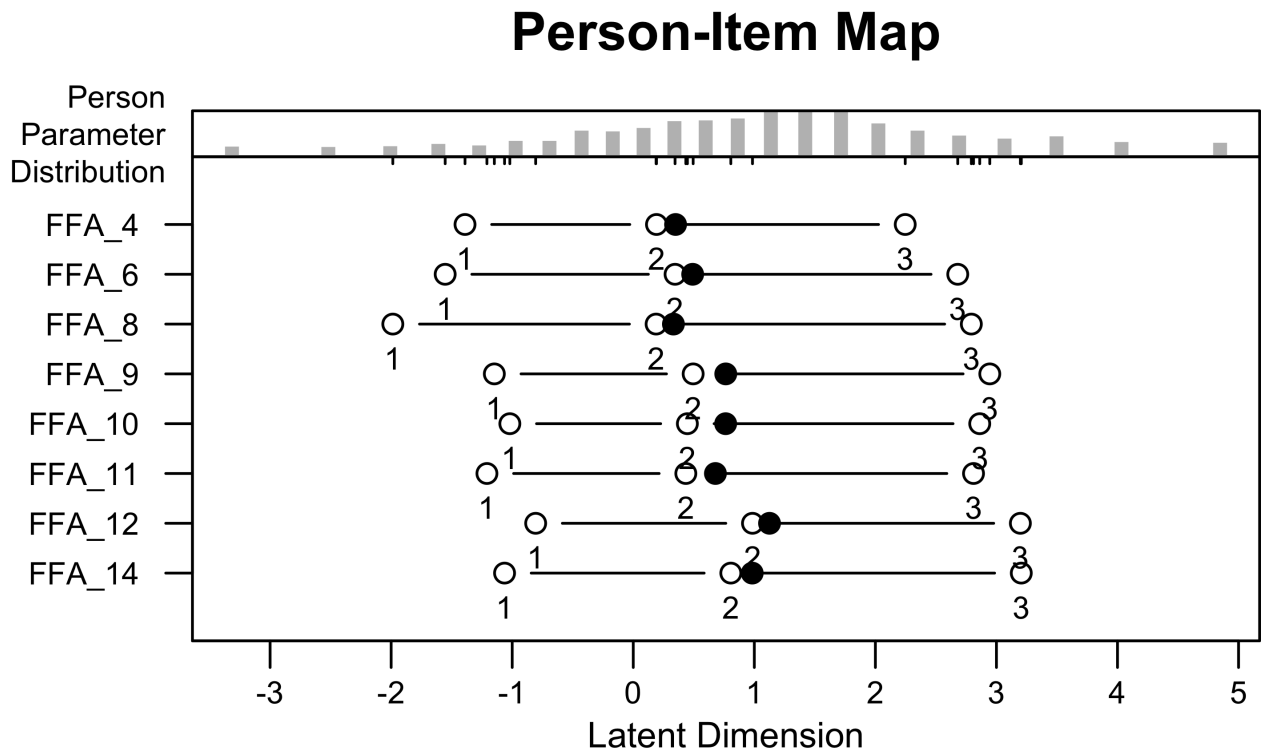
p-value: 0.282

## 6.2.6 Item information

```
plotINFO(ffa_pcm1_acc, legpos = FALSE)
```

Error in plot.new(): figure margins too large

```
plotPimap(ffa_pcm1_acc)
```



## 7 Model comparison

### 7.1 Presence

```
anova(ffa_rsm1_pres, ffa_pcm1_pres)
```

Analysis of Deviances Table

Model 1: PCM(X = ffa13\_pres, se = TRUE)

Model 2: RSM(X = ffa13\_pres, se = TRUE)

cond.	LL	Deviance	npar	LR	df	p-value
-------	----	----------	------	----	----	---------

```
Model 1  -3183.9   6367.8   14
Model 2  -3195.8   6391.5    6 11.846   8  0.1582
```

```
eRm::IC(ffa_rsm1_pres_ppar)
```

Information Criteria:

	value	npar	AIC	BIC	cAIC
joint log-lik	-4494.832	20	9029.663	9127.250	9147.250
marginal log-lik	-5705.088	6	11422.175	11451.681	11457.681
conditional log-lik	-3195.759	6	6403.518	6433.024	6439.024

```
eRm::IC(ffa_pcm1_pres_ppar)
```

Information Criteria:

	value	npar	AIC	BIC	cAIC
joint log-lik	-4483.367	28	9022.735	9159.357	9187.357
marginal log-lik	-5693.242	14	11414.483	11483.331	11497.331
conditional log-lik	-3183.913	14	6395.826	6464.674	6478.674

Small values are better.

That means the PCM models is to be preferred.

## 8 DIF Analysis using ordinal logistic regression

### 8.1 Presence

#### 8.1.1 Gender

```
ffa13_pres_dif_geschlecht <- lordif(ffa13_pres, group = d2$Geschlecht
```

```
Iteration: 1, Log-Lik: -5824.319, Max-Change: 0.42764
Iteration: 2, Log-Lik: -5726.643, Max-Change: 0.31012
Iteration: 3, Log-Lik: -5698.280, Max-Change: 0.16853
Iteration: 4, Log-Lik: -5689.386, Max-Change: 0.08465
```



Iteration: 5, Log-Lik: -5686.866, Max-Change: 0.05223  
Iteration: 6, Log-Lik: -5685.830, Max-Change: 0.04014  
Iteration: 7, Log-Lik: -5685.104, Max-Change: 0.01591  
Iteration: 8, Log-Lik: -5685.026, Max-Change: 0.01001  
Iteration: 9, Log-Lik: -5684.997, Max-Change: 0.00626  
Iteration: 10, Log-Lik: -5684.980, Max-Change: 0.00258  
Iteration: 11, Log-Lik: -5684.976, Max-Change: 0.00296  
Iteration: 12, Log-Lik: -5684.974, Max-Change: 0.00188  
Iteration: 13, Log-Lik: -5684.974, Max-Change: 0.00152  
Iteration: 14, Log-Lik: -5684.973, Max-Change: 0.00067  
Iteration: 15, Log-Lik: -5684.973, Max-Change: 0.00046  
Iteration: 16, Log-Lik: -5684.973, Max-Change: 0.00034  
Iteration: 17, Log-Lik: -5684.973, Max-Change: 0.00028  
Iteration: 18, Log-Lik: -5684.973, Max-Change: 0.00023  
Iteration: 19, Log-Lik: -5684.973, Max-Change: 0.00022  
Iteration: 20, Log-Lik: -5684.973, Max-Change: 0.00023  
Iteration: 21, Log-Lik: -5684.973, Max-Change: 0.00024  
Iteration: 22, Log-Lik: -5684.973, Max-Change: 0.00012  
Iteration: 23, Log-Lik: -5684.973, Max-Change: 0.00010  
Iteration: 24, Log-Lik: -5684.973, Max-Change: 0.00012  
Iteration: 25, Log-Lik: -5684.973, Max-Change: 0.00006  
(mirt) | Iteration: 1, 2 items flagged for DIF (1,4)

Iteration: 1, Log-Lik: -6482.438, Max-Change: 1.84095  
Iteration: 2, Log-Lik: -5768.069, Max-Change: 0.32301  
Iteration: 3, Log-Lik: -5711.589, Max-Change: 0.28219  
Iteration: 4, Log-Lik: -5693.283, Max-Change: 0.16033  
Iteration: 5, Log-Lik: -5683.322, Max-Change: 0.11414  
Iteration: 6, Log-Lik: -5678.856, Max-Change: 0.07636  
Iteration: 7, Log-Lik: -5676.935, Max-Change: 0.03782  
Iteration: 8, Log-Lik: -5676.204, Max-Change: 0.02734  
Iteration: 9, Log-Lik: -5675.814, Max-Change: 0.01969  
Iteration: 10, Log-Lik: -5675.464, Max-Change: 0.01083  
Iteration: 11, Log-Lik: -5675.409, Max-Change: 0.00743  
Iteration: 12, Log-Lik: -5675.377, Max-Change: 0.00532  
Iteration: 13, Log-Lik: -5675.336, Max-Change: 0.00214  
Iteration: 14, Log-Lik: -5675.334, Max-Change: 0.00129  
Iteration: 15, Log-Lik: -5675.333, Max-Change: 0.00105  
Iteration: 16, Log-Lik: -5675.332, Max-Change: 0.00110  
Iteration: 17, Log-Lik: -5675.332, Max-Change: 0.00101  
Iteration: 18, Log-Lik: -5675.332, Max-Change: 0.00099  
Iteration: 19, Log-Lik: -5675.331, Max-Change: 0.00017  
Iteration: 20, Log-Lik: -5675.331, Max-Change: 0.00016  
Iteration: 21, Log-Lik: -5675.331, Max-Change: 0.00015

```

Iteration: 22, Log-Lik: -5675.331, Max-Change: 0.00025
Iteration: 23, Log-Lik: -5675.331, Max-Change: 0.00021
Iteration: 24, Log-Lik: -5675.331, Max-Change: 0.00024
Iteration: 25, Log-Lik: -5675.331, Max-Change: 0.00010
Iteration: 26, Log-Lik: -5675.331, Max-Change: 0.00010
(mirt) | Iteration: 2, 2 items flagged for DIF (1,4)

```

```
print(ffa13_pres_dif_geschlecht)
```

Call:

```

lordif(resp.data = ffa13_pres, group = d2$Geschlecht, pseudo.R2 =
"McFadden",
      minCell = 5)

```

Number of DIF groups: 2

Number of items flagged for DIF: 2 of 5

Items flagged: 1, 4

Number of iterations for purification: 2 of 10

Detection criterion: Chisqr

Threshold: alpha = 0.01

	item	ncat	chi12	chi13	chi23
1	1	4	0.7875	0.0071	0.0017
2	2	4	0.0656	0.1659	0.6522
3	3	4	0.1233	0.2164	0.4075
4	4	4	0.0039	0.0001	0.0016
5	5	4	0.0355	0.0566	0.2494

```
summary(ffa13_pres_dif_geschlecht)
```

Call:

```

lordif(resp.data = ffa13_pres, group = d2$Geschlecht, pseudo.R2 =
"McFadden",
      minCell = 5)

```

\$criterion

[1] "Chisqr"

`$alpha``[1] 0.01``$pseudo.R2``[1] "McFadden"``$R2.change``[1] 0.02``$beta.change``[1] 0.1``$maxIter``[1] 10``$minCell``[1] 5``$stats`

	item	ncat	chi12	chi13	chi23	beta12	pseudo12.McFadden	pseudo13.McFadden
1	1	4	0.7875	0.0071	0.0017	0.0004	0.0000	0.0041
2	2	4	0.0656	0.1659	0.6522	0.0006	0.0013	0.0014
3	3	4	0.1233	0.2164	0.4075	0.0005	0.0009	0.0012
4	4	4	0.0039	0.0001	0.0016	0.0096	0.0034	0.0076
5	5	4	0.0355	0.0566	0.2494	0.0048	0.0018	0.0023
							pseudo23.McFadden	pseudo12.Nagelkerke
							pseudo13.Nagelkerke	pseudo23.Nagelkerke
1			0.0040			0.0000	0.0059	0.0058
2			0.0001			0.0018	0.0019	0.0001
3			0.0003			0.0015	0.0019	0.0004
4			0.0041			0.0040	0.0088	0.0048
5			0.0005			0.0019	0.0025	0.0006
							pseudo12.CoxSnell	pseudo13.CoxSnell
							pseudo23.CoxSnell	df12
								df13

df23

1	0.0000	0.0054	0.0053	1	2
1					
2	0.0016	0.0017	0.0001	1	2
1					
3	0.0013	0.0017	0.0004	1	2
1					
4	0.0036	0.0080	0.0043	1	2
1					
5	0.0017	0.0023	0.0005	1	2
1					

\$flag

[1] TRUE FALSE FALSE TRUE FALSE

\$flag.raw

[1] TRUE FALSE FALSE TRUE FALSE

```
plot(ffa13_pres_dif_geschlecht, labels = c("Frauen", "Männer"))
```

Small DIF only, according to the R squared value.

## 8.1.2 Age

```
ffa13_pres_dif_age <- lordif(ffa13_pres, group = d2$Alter_medsplit, p
```

```
Iteration: 1, Log-Lik: -5824.319, Max-Change: 0.42764
Iteration: 2, Log-Lik: -5726.643, Max-Change: 0.31012
Iteration: 3, Log-Lik: -5698.280, Max-Change: 0.16853
Iteration: 4, Log-Lik: -5689.386, Max-Change: 0.08465
Iteration: 5, Log-Lik: -5686.866, Max-Change: 0.05223
Iteration: 6, Log-Lik: -5685.830, Max-Change: 0.04014
Iteration: 7, Log-Lik: -5685.104, Max-Change: 0.01591
Iteration: 8, Log-Lik: -5685.026, Max-Change: 0.01001
Iteration: 9, Log-Lik: -5684.997, Max-Change: 0.00626
Iteration: 10, Log-Lik: -5684.980, Max-Change: 0.00258
Iteration: 11, Log-Lik: -5684.976, Max-Change: 0.00296
Iteration: 12, Log-Lik: -5684.974, Max-Change: 0.00188
Iteration: 13, Log-Lik: -5684.974, Max-Change: 0.00152
Iteration: 14, Log-Lik: -5684.973, Max-Change: 0.00067
Iteration: 15, Log-Lik: -5684.973, Max-Change: 0.00046
```

Iteration: 16, Log-Lik: -5684.973, Max-Change: 0.00034  
Iteration: 17, Log-Lik: -5684.973, Max-Change: 0.00028  
Iteration: 18, Log-Lik: -5684.973, Max-Change: 0.00023  
Iteration: 19, Log-Lik: -5684.973, Max-Change: 0.00022  
Iteration: 20, Log-Lik: -5684.973, Max-Change: 0.00023  
Iteration: 21, Log-Lik: -5684.973, Max-Change: 0.00024  
Iteration: 22, Log-Lik: -5684.973, Max-Change: 0.00012  
Iteration: 23, Log-Lik: -5684.973, Max-Change: 0.00010  
Iteration: 24, Log-Lik: -5684.973, Max-Change: 0.00012  
Iteration: 25, Log-Lik: -5684.973, Max-Change: 0.00006  
(mirt) | Iteration: 1, 3 items flagged for DIF (1,2,3)

Iteration: 1, Log-Lik: -6903.604, Max-Change: 2.34723  
Iteration: 2, Log-Lik: -5805.344, Max-Change: 0.44722  
Iteration: 3, Log-Lik: -5738.895, Max-Change: 0.30599  
Iteration: 4, Log-Lik: -5691.169, Max-Change: 0.17286  
Iteration: 5, Log-Lik: -5671.489, Max-Change: 0.13734  
Iteration: 6, Log-Lik: -5663.006, Max-Change: 0.06553  
Iteration: 7, Log-Lik: -5658.182, Max-Change: 0.10543  
Iteration: 8, Log-Lik: -5655.064, Max-Change: 0.05100  
Iteration: 9, Log-Lik: -5653.288, Max-Change: 0.03652  
Iteration: 10, Log-Lik: -5651.528, Max-Change: 0.02980  
Iteration: 11, Log-Lik: -5651.169, Max-Change: 0.01739  
Iteration: 12, Log-Lik: -5650.976, Max-Change: 0.01236  
Iteration: 13, Log-Lik: -5650.713, Max-Change: 0.00528  
Iteration: 14, Log-Lik: -5650.699, Max-Change: 0.00327  
Iteration: 15, Log-Lik: -5650.692, Max-Change: 0.00276  
Iteration: 16, Log-Lik: -5650.682, Max-Change: 0.00180  
Iteration: 17, Log-Lik: -5650.681, Max-Change: 0.00145  
Iteration: 18, Log-Lik: -5650.681, Max-Change: 0.00111  
Iteration: 19, Log-Lik: -5650.681, Max-Change: 0.00022  
Iteration: 20, Log-Lik: -5650.681, Max-Change: 0.00018  
Iteration: 21, Log-Lik: -5650.681, Max-Change: 0.00017  
Iteration: 22, Log-Lik: -5650.681, Max-Change: 0.00018  
Iteration: 23, Log-Lik: -5650.681, Max-Change: 0.00015  
Iteration: 24, Log-Lik: -5650.681, Max-Change: 0.00014  
Iteration: 25, Log-Lik: -5650.681, Max-Change: 0.00013  
Iteration: 26, Log-Lik: -5650.681, Max-Change: 0.00012  
Iteration: 27, Log-Lik: -5650.681, Max-Change: 0.00012  
Iteration: 28, Log-Lik: -5650.681, Max-Change: 0.00011  
Iteration: 29, Log-Lik: -5650.681, Max-Change: 0.00010  
Iteration: 30, Log-Lik: -5650.681, Max-Change: 0.00010  
(mirt) | Iteration: 2, 3 items flagged for DIF (1,2,3)

```
print(ffa13_pres_dif_age)
```

Call:

```
lordif(resp.data = ffa13_pres, group = d2$Alter_medsplit, pseudo.R2 =
"McFadden",
  minCell = 5)
```

Number of DIF groups: 2

Number of items flagged for DIF: 3 of 5

Items flagged: 1, 2, 3

Number of iterations for purification: 2 of 10

Detection criterion: Chisqr

Threshold: alpha = 0.01

	item	ncat	chi12	chi13	chi23
1	1	4	0.0000	0.0000	0.0028
2	2	4	0.0015	0.0056	0.5810
3	3	4	0.0000	0.0000	0.0608
4	4	4	0.6726	0.8789	0.7779
5	5	4	0.2395	0.4419	0.6171

```
summary(ffa13_pres_dif_age)
```

Call:

```
lordif(resp.data = ffa13_pres, group = d2$Alter_medsplit, pseudo.R2 =
"McFadden",
  minCell = 5)
```

\$criterion

[1] "Chisqr"

\$alpha

[1] 0.01

\$pseudo.R2

[1] "McFadden"

\$R2.change

```
[1] 0.02
```

```
$beta.change
```

```
[1] 0.1
```

```
$maxIter
```

```
[1] 10
```

```
$minCell
```

```
[1] 5
```

```
$stats
```

```
  item ncat  chi12  chi13  chi23 beta12 pseudo12.McFadden
pseudo13.McFadden
```

```
1    1    4 0.0000 0.0000 0.0028 0.0188          0.0157
0.0194
```

```
2    2    4 0.0015 0.0056 0.5810 0.0114          0.0039
0.0040
```

```
3    3    4 0.0000 0.0000 0.0608 0.0183          0.0075
0.0089
```

```
4    4    4 0.6726 0.8789 0.7779 0.0005          0.0001
0.0001
```

```
5    5    4 0.2395 0.4419 0.6171 0.0004          0.0006
0.0007
```

```
  pseudo23.McFadden pseudo12.Nagelkerke pseudo13.Nagelkerke
pseudo23.Nagelkerke
```

```
1          0.0037          0.0220          0.0270
0.0050
```

```
2          0.0001          0.0052          0.0054
0.0002
```

```
3          0.0014          0.0113          0.0134
0.0021
```

```
4          0.0000          0.0001          0.0001
0.0000
```

```
5          0.0001          0.0006          0.0007
0.0001
```

```
  pseudo12.CoxSnell pseudo13.CoxSnell pseudo23.CoxSnell df12 df13
df23
```

```
1          0.0200          0.0246          0.0046    1    2
1
```

```
2          0.0048          0.0050          0.0001    1    2
1
```

```
3          0.0104          0.0123          0.0019    1    2
1
```

4	0.0001	0.0001	0.0000	1	2
1					
5	0.0005	0.0006	0.0001	1	2
1					

```
$flag
```

```
[1] TRUE TRUE TRUE FALSE FALSE
```

```
$flag.raw
```

```
[1] TRUE TRUE TRUE FALSE FALSE
```

```
plot(ffa13_pres_dif_age, labels = c("Frauen", "Männer"))
```

Small DIF only, according to the R squared value.

## 8.2 Acceptance

### 8.2.1 Gender

Small DIF only, according to the R squared value.

```
ffa13_acc_dif_geschlecht <- lordif(ffa13_acc, group = d2$Geschlecht,
```

```
Iteration: 1, Log-Lik: -8872.140, Max-Change: 0.70854
Iteration: 2, Log-Lik: -8637.150, Max-Change: 0.29476
Iteration: 3, Log-Lik: -8584.463, Max-Change: 0.16797
Iteration: 4, Log-Lik: -8564.003, Max-Change: 0.09840
Iteration: 5, Log-Lik: -8555.357, Max-Change: 0.06883
Iteration: 6, Log-Lik: -8550.847, Max-Change: 0.04964
Iteration: 7, Log-Lik: -8546.419, Max-Change: 0.02507
Iteration: 8, Log-Lik: -8546.008, Max-Change: 0.01598
Iteration: 9, Log-Lik: -8545.777, Max-Change: 0.01082
Iteration: 10, Log-Lik: -8545.592, Max-Change: 0.00642
Iteration: 11, Log-Lik: -8545.553, Max-Change: 0.00470
Iteration: 12, Log-Lik: -8545.531, Max-Change: 0.00346
Iteration: 13, Log-Lik: -8545.508, Max-Change: 0.00191
Iteration: 14, Log-Lik: -8545.505, Max-Change: 0.00271
Iteration: 15, Log-Lik: -8545.504, Max-Change: 0.00145
Iteration: 16, Log-Lik: -8545.503, Max-Change: 0.00073
Iteration: 17, Log-Lik: -8545.502, Max-Change: 0.00045
```



Iteration: 18, Log-Lik: -8545.502, Max-Change: 0.00035  
Iteration: 19, Log-Lik: -8545.502, Max-Change: 0.00040  
Iteration: 20, Log-Lik: -8545.502, Max-Change: 0.00038  
Iteration: 21, Log-Lik: -8545.502, Max-Change: 0.00049  
Iteration: 22, Log-Lik: -8545.502, Max-Change: 0.00034  
Iteration: 23, Log-Lik: -8545.501, Max-Change: 0.00045  
Iteration: 24, Log-Lik: -8545.501, Max-Change: 0.00052  
Iteration: 25, Log-Lik: -8545.501, Max-Change: 0.00029  
Iteration: 26, Log-Lik: -8545.501, Max-Change: 0.00033  
Iteration: 27, Log-Lik: -8545.501, Max-Change: 0.00041  
Iteration: 28, Log-Lik: -8545.501, Max-Change: 0.00022  
Iteration: 29, Log-Lik: -8545.501, Max-Change: 0.00027  
Iteration: 30, Log-Lik: -8545.501, Max-Change: 0.00033  
Iteration: 31, Log-Lik: -8545.501, Max-Change: 0.00018  
Iteration: 32, Log-Lik: -8545.501, Max-Change: 0.00021  
Iteration: 33, Log-Lik: -8545.501, Max-Change: 0.00025  
Iteration: 34, Log-Lik: -8545.501, Max-Change: 0.00014  
Iteration: 35, Log-Lik: -8545.501, Max-Change: 0.00016  
Iteration: 36, Log-Lik: -8545.501, Max-Change: 0.00020  
Iteration: 37, Log-Lik: -8545.501, Max-Change: 0.00011  
Iteration: 38, Log-Lik: -8545.501, Max-Change: 0.00013  
Iteration: 39, Log-Lik: -8545.501, Max-Change: 0.00016  
Iteration: 40, Log-Lik: -8545.501, Max-Change: 0.00009  
(mirt) | Iteration: 1, 1 items flagged for DIF (3)

Iteration: 1, Log-Lik: -9286.267, Max-Change: 2.52636  
Iteration: 2, Log-Lik: -8625.737, Max-Change: 0.44941  
Iteration: 3, Log-Lik: -8573.205, Max-Change: 0.20548  
Iteration: 4, Log-Lik: -8556.243, Max-Change: 0.09924  
Iteration: 5, Log-Lik: -8548.733, Max-Change: 0.07911  
Iteration: 6, Log-Lik: -8544.225, Max-Change: 0.04588  
Iteration: 7, Log-Lik: -8542.665, Max-Change: 0.03566  
Iteration: 8, Log-Lik: -8541.171, Max-Change: 0.02853  
Iteration: 9, Log-Lik: -8540.204, Max-Change: 0.02383  
Iteration: 10, Log-Lik: -8539.038, Max-Change: 0.02855  
Iteration: 11, Log-Lik: -8538.820, Max-Change: 0.03268  
Iteration: 12, Log-Lik: -8538.672, Max-Change: 0.00695  
Iteration: 13, Log-Lik: -8538.591, Max-Change: 0.00567  
Iteration: 14, Log-Lik: -8538.530, Max-Change: 0.00472  
Iteration: 15, Log-Lik: -8538.487, Max-Change: 0.00450  
Iteration: 16, Log-Lik: -8538.404, Max-Change: 0.00582  
Iteration: 17, Log-Lik: -8538.395, Max-Change: 0.00223  
Iteration: 18, Log-Lik: -8538.391, Max-Change: 0.00159  
Iteration: 19, Log-Lik: -8538.383, Max-Change: 0.00089

```
Iteration: 20, Log-Lik: -8538.382, Max-Change: 0.00072
Iteration: 21, Log-Lik: -8538.382, Max-Change: 0.00064
Iteration: 22, Log-Lik: -8538.380, Max-Change: 0.00029
Iteration: 23, Log-Lik: -8538.380, Max-Change: 0.00018
Iteration: 24, Log-Lik: -8538.380, Max-Change: 0.00015
Iteration: 25, Log-Lik: -8538.380, Max-Change: 0.00009
(mirt) | Iteration: 2, 1 items flagged for DIF (3)
```

```
print(ffa13_acc_dif_geschlecht)
```

Call:

```
lordif(resp.data = ffa13_acc, group = d2$Geschlecht, pseudo.R2 =
"McFadden",
      minCell = 5)
```

Number of DIF groups: 2

Number of items flagged for DIF: 1 of 8

Items flagged: 3

Number of iterations for purification: 2 of 10

Detection criterion: Chisqr

Threshold: alpha = 0.01

	item	ncat	chi12	chi13	chi23
1	1	4	0.0307	0.0622	0.3468
2	2	4	0.4105	0.2641	0.1588
3	3	4	0.0162	0.0003	0.0014
4	4	4	0.0676	0.1625	0.5880
5	5	4	0.0723	0.1014	0.2456
6	6	4	0.9911	0.9530	0.7566
7	7	4	0.0585	0.1525	0.6691
8	8	4	0.0710	0.0983	0.2402

```
summary(ffa13_acc_dif_geschlecht)
```

Call:

```
lordif(resp.data = ffa13_acc, group = d2$Geschlecht, pseudo.R2 =
"McFadden",
      minCell = 5)
```

```
$criterion
[1] "Chisqr"
```

```
$alpha
[1] 0.01
```

```
$pseudo.R2
[1] "McFadden"
```

```
$R2.change
[1] 0.02
```

```
$beta.change
[1] 0.1
```

```
$maxIter
[1] 10
```

```
$minCell
[1] 5
```

```
$stats
  item ncat  chi12  chi13  chi23 beta12 pseudo12.McFadden
pseudo13.McFadden
1    1    4 0.0307 0.0622 0.3468 0.0006          0.0019
0.0022
2    2    4 0.4105 0.2641 0.1588 0.0003          0.0003
0.0011
3    3    4 0.0162 0.0003 0.0014 0.0064          0.0025
0.0069
4    4    4 0.0676 0.1625 0.5880 0.0039          0.0014
0.0015
5    5    4 0.0723 0.1014 0.2456 0.0050          0.0013
0.0018
6    6    4 0.9911 0.9530 0.7566 0.0000          0.0000
0.0000
7    7    4 0.0585 0.1525 0.6691 0.0008          0.0014
0.0015
8    8    4 0.0710 0.0983 0.2402 0.0044          0.0013
0.0019
  pseudo23.McFadden pseudo12.Nagelkerke pseudo13.Nagelkerke
pseudo23.Nagelkerke
1              0.0004              0.0027              0.0033
```

0.0005

2	0.0008	0.0004	0.0014
---	--------	--------	--------

0.0011

3	0.0044	0.0042	0.0115
---	--------	--------	--------

0.0073

4	0.0001	0.0015	0.0016
---	--------	--------	--------

0.0001

5	0.0005	0.0017	0.0024
---	--------	--------	--------

0.0007

6	0.0000	0.0000	0.0000
---	--------	--------	--------

0.0000

7	0.0001	0.0017	0.0018
---	--------	--------	--------

0.0001

8	0.0006	0.0022	0.0031
---	--------	--------	--------

0.0009

	pseudo12.CoxSnell	pseudo13.CoxSnell	pseudo23.CoxSnell	df12	df13
df23					

1	0.0025	0.0030	0.0005	1	2
---	--------	--------	--------	---	---

1

2	0.0003	0.0013	0.0010	1	2
---	--------	--------	--------	---	---

1

3	0.0038	0.0103	0.0066	1	2
---	--------	--------	--------	---	---

1

4	0.0014	0.0015	0.0001	1	2
---	--------	--------	--------	---	---

1

5	0.0015	0.0022	0.0006	1	2
---	--------	--------	--------	---	---

1

6	0.0000	0.0000	0.0000	1	2
---	--------	--------	--------	---	---

1

7	0.0016	0.0016	0.0001	1	2
---	--------	--------	--------	---	---

1

8	0.0020	0.0028	0.0008	1	2
---	--------	--------	--------	---	---

1

\$flag

[1] FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE

\$flag.raw

[1] FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE

```
plot(ffa13_acc_dif_geschlecht, labels = c("Frauen", "Männer"))
```

Small DIF only, according to the R squared value.

## 8.2.2 Age

```
ffa13_acc_dif_age <- lordif(ffa13_pres, group = d2$Alter_medsplit, ps
```

```
Iteration: 1, Log-Lik: -5824.319, Max-Change: 0.42764
Iteration: 2, Log-Lik: -5726.643, Max-Change: 0.31012
Iteration: 3, Log-Lik: -5698.280, Max-Change: 0.16853
Iteration: 4, Log-Lik: -5689.386, Max-Change: 0.08465
Iteration: 5, Log-Lik: -5686.866, Max-Change: 0.05223
Iteration: 6, Log-Lik: -5685.830, Max-Change: 0.04014
Iteration: 7, Log-Lik: -5685.104, Max-Change: 0.01591
Iteration: 8, Log-Lik: -5685.026, Max-Change: 0.01001
Iteration: 9, Log-Lik: -5684.997, Max-Change: 0.00626
Iteration: 10, Log-Lik: -5684.980, Max-Change: 0.00258
Iteration: 11, Log-Lik: -5684.976, Max-Change: 0.00296
Iteration: 12, Log-Lik: -5684.974, Max-Change: 0.00188
Iteration: 13, Log-Lik: -5684.974, Max-Change: 0.00152
Iteration: 14, Log-Lik: -5684.973, Max-Change: 0.00067
Iteration: 15, Log-Lik: -5684.973, Max-Change: 0.00046
Iteration: 16, Log-Lik: -5684.973, Max-Change: 0.00034
Iteration: 17, Log-Lik: -5684.973, Max-Change: 0.00028
Iteration: 18, Log-Lik: -5684.973, Max-Change: 0.00023
Iteration: 19, Log-Lik: -5684.973, Max-Change: 0.00022
Iteration: 20, Log-Lik: -5684.973, Max-Change: 0.00023
Iteration: 21, Log-Lik: -5684.973, Max-Change: 0.00024
Iteration: 22, Log-Lik: -5684.973, Max-Change: 0.00012
Iteration: 23, Log-Lik: -5684.973, Max-Change: 0.00010
Iteration: 24, Log-Lik: -5684.973, Max-Change: 0.00012
Iteration: 25, Log-Lik: -5684.973, Max-Change: 0.00006
(mirt) | Iteration: 1, 3 items flagged for DIF (1,2,3)
```

```
Iteration: 1, Log-Lik: -6903.604, Max-Change: 2.34723
Iteration: 2, Log-Lik: -5805.344, Max-Change: 0.44722
Iteration: 3, Log-Lik: -5738.895, Max-Change: 0.30599
Iteration: 4, Log-Lik: -5691.169, Max-Change: 0.17286
Iteration: 5, Log-Lik: -5671.489, Max-Change: 0.13734
Iteration: 6, Log-Lik: -5663.006, Max-Change: 0.06553
Iteration: 7, Log-Lik: -5658.182, Max-Change: 0.10543
Iteration: 8, Log-Lik: -5655.064, Max-Change: 0.05100
Iteration: 9, Log-Lik: -5653.288, Max-Change: 0.03652
```

```

Iteration: 10, Log-Lik: -5651.528, Max-Change: 0.02980
Iteration: 11, Log-Lik: -5651.169, Max-Change: 0.01739
Iteration: 12, Log-Lik: -5650.976, Max-Change: 0.01236
Iteration: 13, Log-Lik: -5650.713, Max-Change: 0.00528
Iteration: 14, Log-Lik: -5650.699, Max-Change: 0.00327
Iteration: 15, Log-Lik: -5650.692, Max-Change: 0.00276
Iteration: 16, Log-Lik: -5650.682, Max-Change: 0.00180
Iteration: 17, Log-Lik: -5650.681, Max-Change: 0.00145
Iteration: 18, Log-Lik: -5650.681, Max-Change: 0.00111
Iteration: 19, Log-Lik: -5650.681, Max-Change: 0.00022
Iteration: 20, Log-Lik: -5650.681, Max-Change: 0.00018
Iteration: 21, Log-Lik: -5650.681, Max-Change: 0.00017
Iteration: 22, Log-Lik: -5650.681, Max-Change: 0.00018
Iteration: 23, Log-Lik: -5650.681, Max-Change: 0.00015
Iteration: 24, Log-Lik: -5650.681, Max-Change: 0.00014
Iteration: 25, Log-Lik: -5650.681, Max-Change: 0.00013
Iteration: 26, Log-Lik: -5650.681, Max-Change: 0.00012
Iteration: 27, Log-Lik: -5650.681, Max-Change: 0.00012
Iteration: 28, Log-Lik: -5650.681, Max-Change: 0.00011
Iteration: 29, Log-Lik: -5650.681, Max-Change: 0.00010
Iteration: 30, Log-Lik: -5650.681, Max-Change: 0.00010
(mirt) | Iteration: 2, 3 items flagged for DIF (1,2,3)

```

```
print(ffa13_acc_dif_age)
```

Call:

```
lordif(resp.data = ffa13_pres, group = d2$Alter_medsplit, pseudo.R2 =
"McFadden",
      minCell = 5)
```

Number of DIF groups: 2

Number of items flagged for DIF: 3 of 5

Items flagged: 1, 2, 3

Number of iterations for purification: 2 of 10

Detection criterion: Chisqr

Threshold: alpha = 0.01

```
item ncat  chi12  chi13  chi23
```

1	1	4	0.0000	0.0000	0.0028
2	2	4	0.0015	0.0056	0.5810
3	3	4	0.0000	0.0000	0.0608
4	4	4	0.6726	0.8789	0.7779
5	5	4	0.2395	0.4419	0.6171

```
summary(ffa13_acc_dif_age)
```

Call:

```
lordif(resp.data = ffa13_pres, group = d2$Alter_medsplit, pseudo.R2 =
"McFadden",
      minCell = 5)
```

\$criterion

```
[1] "Chisqr"
```

\$alpha

```
[1] 0.01
```

\$pseudo.R2

```
[1] "McFadden"
```

\$R2.change

```
[1] 0.02
```

\$beta.change

```
[1] 0.1
```

\$maxIter

```
[1] 10
```

\$minCell

```
[1] 5
```

\$stats

	item	ncat	chi12	chi13	chi23	beta12	pseudo12.McFadden	pseudo13.McFadden
1	1	4	0.0000	0.0000	0.0028	0.0188	0.0157	0.0194
2	2	4	0.0015	0.0056	0.5810	0.0114	0.0039	0.0040
3	3	4	0.0000	0.0000	0.0608	0.0183	0.0075	0.0089

```

4      4      4 0.6726 0.8789 0.7779 0.0005      0.0001
0.0001
5      5      4 0.2395 0.4419 0.6171 0.0004      0.0006
0.0007
pseudo23.McFadden pseudo12.Nagelkerke pseudo13.Nagelkerke
pseudo23.Nagelkerke
1      0.0037      0.0220      0.0270
0.0050
2      0.0001      0.0052      0.0054
0.0002
3      0.0014      0.0113      0.0134
0.0021
4      0.0000      0.0001      0.0001
0.0000
5      0.0001      0.0006      0.0007
0.0001

```

```

pseudo12.CoxSnell pseudo13.CoxSnell pseudo23.CoxSnell df12 df13
df23
1      0.0200      0.0246      0.0046      1      2
1
2      0.0048      0.0050      0.0001      1      2
1
3      0.0104      0.0123      0.0019      1      2
1
4      0.0001      0.0001      0.0000      1      2
1
5      0.0005      0.0006      0.0001      1      2
1

```

```
$flag
```

```
[1] TRUE TRUE TRUE FALSE FALSE
```

```
$flag.raw
```

```
[1] TRUE TRUE TRUE FALSE FALSE
```

```
plot(ffa13_acc_dif_age, labels = c("Frauen", "Männer"))
```

Small DIF only, according to the R squared value.

## 9 Dimensionality

### 9.1 EFA



## 9.2 Determine number of factors

2 factors, oblimin rotation, ML factor scores:

```
ffa_fa <- psych::fa(ffa13_items, nfactors = 2, rotate = "oblimin", fm
print(ffa_fa)
```

Factor Analysis using method = ml

Call: psych::fa(r = ffa13\_items, nfactors = 2, rotate = "oblimin",  
fm = "ml")

Standardized loadings (pattern matrix) based upon correlation matrix

	ML1	ML2	h2	u2	com
FFA_1	0.31	0.29	0.30	0.70	2.0
FFA_2	0.02	0.68	0.48	0.52	1.0
FFA_3	0.10	0.54	0.37	0.63	1.1
FFA_4	0.68	-0.07	0.41	0.59	1.0
FFA_5	0.53	0.20	0.45	0.55	1.3
FFA_6	0.72	-0.07	0.47	0.53	1.0
FFA_7	0.54	0.20	0.47	0.53	1.3
FFA_8	0.44	0.14	0.28	0.72	1.2
FFA_9	0.76	-0.13	0.48	0.52	1.1
FFA_10	0.56	0.16	0.45	0.55	1.2
FFA_11	0.69	0.00	0.47	0.53	1.0
FFA_12	0.60	0.10	0.43	0.57	1.1
FFA_14	0.46	0.13	0.31	0.69	1.2

	ML1	ML2
SS loadings	4.07	1.29
Proportion Var	0.31	0.10
Cumulative Var	0.31	0.41
Proportion Explained	0.76	0.24
Cumulative Proportion	0.76	1.00

With factor correlations of

	ML1	ML2
ML1	1.00	0.61
ML2	0.61	1.00

Mean item complexity = 1.2

Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the null model are 78 and the objective function was 4.32 with Chi Square of 4341.12

The degrees of freedom for the model are 53 and the objective function was 0.19

The root mean square of the residuals (RMSR) is 0.03

The df corrected root mean square of the residuals is 0.03

The harmonic number of observations is 1010 with the empirical chi square 130.4 with prob < 1.8e-08

The total number of observations was 1010 with Likelihood Chi Square = 186.49 with prob < 9.3e-17

Tucker Lewis Index of factoring reliability = 0.954

RMSEA index = 0.05 and the 90 % confidence intervals are 0.042 0.058

BIC = -180.15

Fit based upon off diagonal values = 0.99

Measures of factor score adequacy

	ML1	ML2
Correlation of (regression) scores with factors	0.94	0.84
Multiple R square of scores with factors	0.88	0.70
Minimum correlation of possible factor scores	0.76	0.41

```
print(ffa_fa$loadings, cutoff = 0.2)
```

Loadings:

	ML1	ML2
FFA_1	0.314	0.292
FFA_2		0.678
FFA_3		0.543
FFA_4	0.683	
FFA_5	0.532	
FFA_6	0.722	
FFA_7	0.540	0.202
FFA_8	0.437	
FFA_9	0.762	
FFA_10	0.559	
FFA_11	0.685	
FFA_12	0.596	
FFA_14	0.465	

	ML1	ML2
SS loadings	3.795	1.018
Proportion Var	0.292	0.078
Cumulative Var	0.292	0.370

Try different number of factors:

```
ffa_div_fa <- nfactors(ffa13_items, n = 5, fm = "ml")
ffa_div_fa
```

Number of factors

Call: vss(x = x, n = n, rotate = rotate, diagonal = diagonal, fm = fm,

n.obs = n.obs, plot = FALSE, title = title, use = use, cor = cor)

VSS complexity 1 achieves a maximum of 0.84 with 1 factors

VSS complexity 2 achieves a maximum of 0.87 with 2 factors

The Velicer MAP achieves a minimum of 0.01 with 1 factors

Empirical BIC achieves a minimum of -236.24 with 2 factors

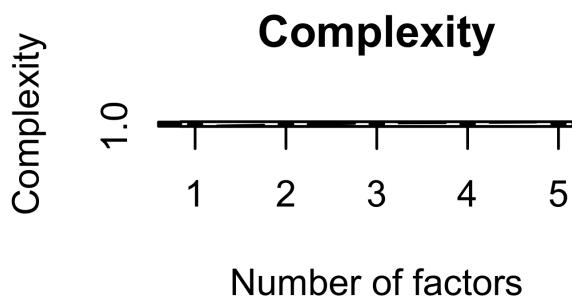
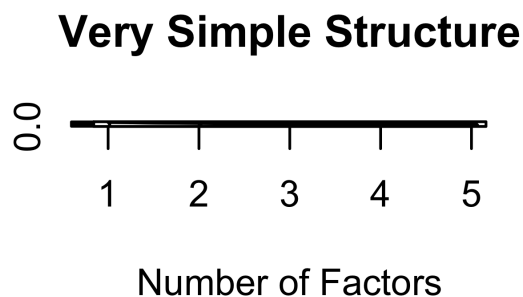
Sample Size adjusted BIC achieves a minimum of -62.5 with 5 factors

Statistics by number of factors

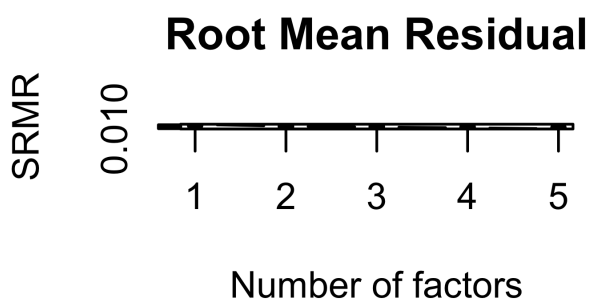
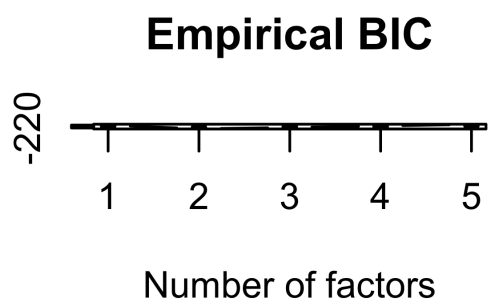
	vss1	vss2	map	dof	chisq	prob	sqresid	fit	RMSEA	BIC	SABIC
complex											
1	0.84	0.00	0.012	65	326	1.8e-36	5.5	0.84	0.0631	-123	83
1.0											
2	0.63	0.87	0.020	53	186	9.3e-17	4.7	0.87	0.0499	-180	-12
1.5											
3	0.37	0.73	0.030	42	119	3.2e-09	4.3	0.88	0.0425	-172	-39
2.2											
4	0.36	0.65	0.041	32	66	4.0e-04	4.0	0.89	0.0323	-156	-54
2.3											
5	0.30	0.56	0.061	23	24	4.3e-01	3.6	0.90	0.0048	-136	-62
2.6											

	eChisq	SRMR	eCRMS	eBIC
1	288	0.0428	0.047	-161
2	130	0.0288	0.035	-236
3	81	0.0227	0.031	-210
4	44	0.0166	0.026	-178
5	14	0.0093	0.017	-146

Very Simple Structure F



Empirical BIC

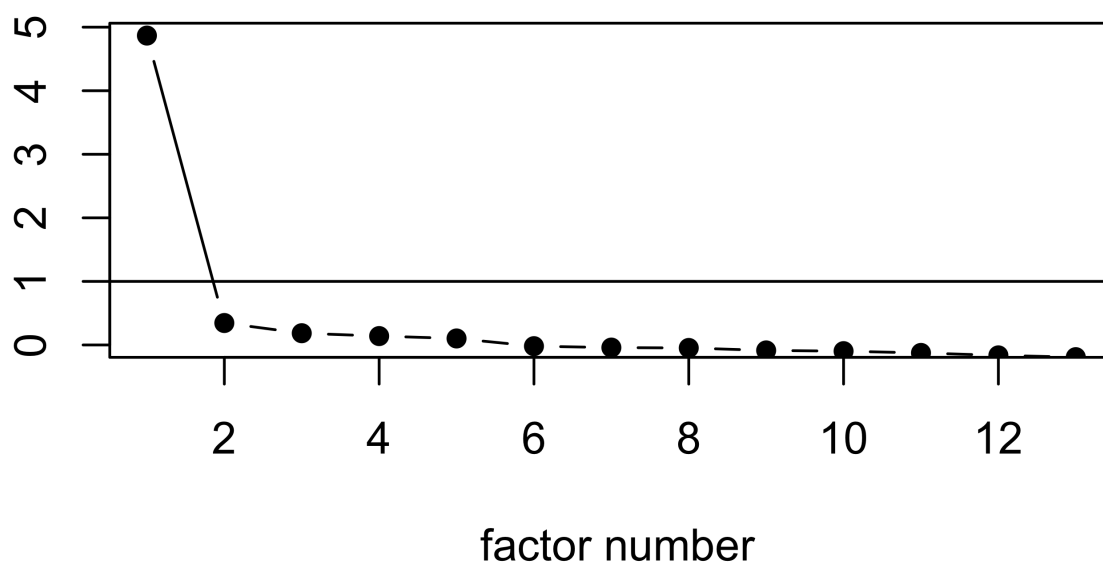


This analyses both supports the 1- and the 2-F solution.

```
scee(ffa13_items, pc = FALSE)
```

## Scree plot

Eigen values of factors



Screeplot (in combination with Kaiser criterion) suggests a unidimensional solution.

```
vss(ffa13_items, fm = "ml", n = 3, plot = FALSE)
```

### Very Simple Structure

Call: `vss(x = ffa13_items, n = 3, fm = "ml", plot = FALSE)`

VSS complexity 1 achieves a maximum of 0.84 with 1 factors

VSS complexity 2 achieves a maximum of 0.87 with 2 factors

The Velicer MAP achieves a minimum of 0.01 with 1 factors

BIC achieves a minimum of -180.15 with 2 factors

Sample Size adjusted BIC achieves a minimum of -38.62 with 3 factors

### Statistics by number of factors

	vss1	vss2	map	dof	chisq	prob	sqresid	fit	RMSEA	BIC	SABIC
complex											
1	0.84	0.00	0.012	65	326	1.8e-36	5.5	0.84	0.063	-123	83
1.0											
2	0.63	0.87	0.020	53	186	9.3e-17	4.7	0.87	0.050	-180	-12
1.5											
3	0.37	0.73	0.030	42	119	3.2e-09	4.3	0.88	0.042	-172	-39
2.2											
	eChisq	SRMR	eCRMS	eBIC							
1	288	0.043	0.047	-161							
2	130	0.029	0.035	-236							
3	81	0.023	0.031	-210							

VSS seems to suggest a 1 factor solution too.

MAP favors the 1 factor solution too.

## 9.2.1 Goodness of fit

```
summary(ffa_fa)
```

Factor analysis with Call: `psych::fa(r = ffa13_items, nfactors = 2, rotate = "oblimin", fm = "ml")`

Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the model is 53 and the objective

function was 0.19

The number of observations was 1010 with Chi Square = 186.49 with prob < 9.3e-17

The root mean square of the residuals (RMSA) is 0.03

The df corrected root mean square of the residuals is 0.03

Tucker Lewis Index of factoring reliability = 0.954

RMSEA index = 0.05 and the 10 % confidence intervals are 0.042 0.058

BIC = -180.15

With factor correlations of

ML1 ML2

ML1 1.00 0.61

ML2 0.61 1.00

## 9.3 CFA

### 9.3.1 2F model

```
ffa_mod <- '
pres =~ FFA_1 + FFA_2 + FFA_3 + FFA_5 + FFA_7
acc =~ FFA_4 + FFA_6 + FFA_8 + FFA_9 + FFA_10 + FFA_11 + FFA_12 + FFA_13

ffa_cfa <- lavaan::cfa(ffa_mod, data = ffa_items2, ordered = TRUE)
#ffa_cfa <- lavaan::cfa(ffa_mod, data = ffa_items2)

ffa_cfa
```

lavaan 0.6-12 ended normally after 32 iterations

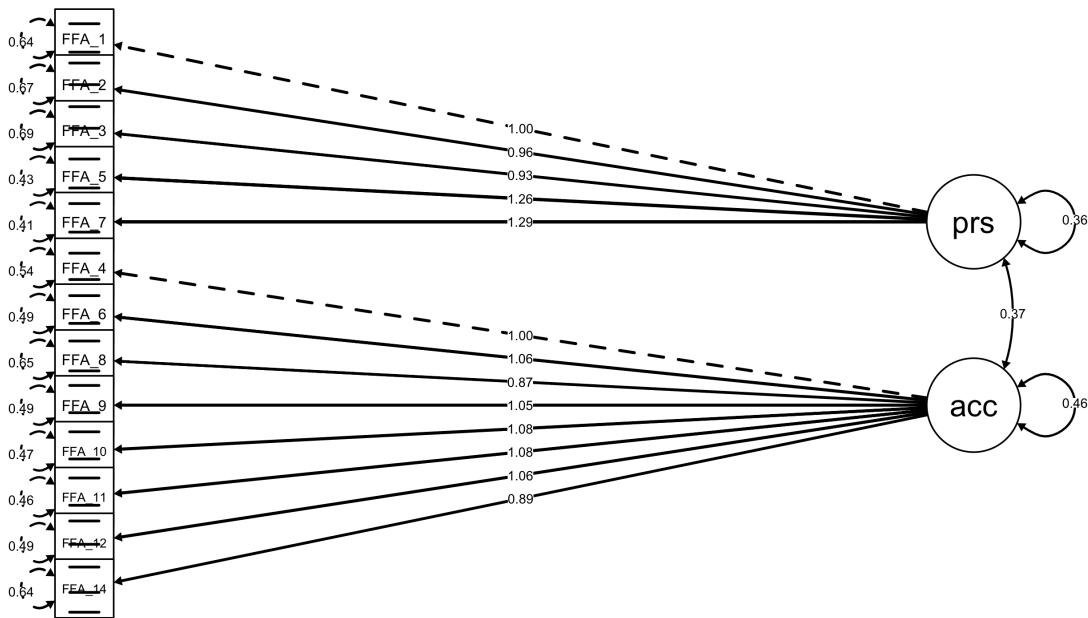
Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	53
Number of observations	1010

Model Test User Model:

	Standard	Robust
Test Statistic	235.356	432.002

Degrees of freedom	64	64
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.555
Shift parameter		8.057
simple second-order correction		

```
semPaths(ffa_cfa, what = "est", intercepts = FALSE,
          rotation = 4, edge.color = 1, fade = FALSE,
          edge.label.cex = .5, edge.width = .3)
```



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

lavaan 0.6-12 ended normally after 32 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	53
Number of observations	1010

Model Test User Model:

	Standard	Robust
Test Statistic	235.356	432.002

Degrees of freedom	64	64
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.555
Shift parameter		8.057
simple second-order correction		

## Model Test Baseline Model:

Test statistic	23657.526	8990.511
Degrees of freedom	78	78
P-value	0.000	0.000
Scaling correction factor		2.646

## User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.993	0.959
Tucker-Lewis Index (TLI)	0.991	0.950
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

## Root Mean Square Error of Approximation:

RMSEA	0.052	0.075
90 Percent confidence interval - lower	0.045	0.069
90 Percent confidence interval - upper	0.059	0.082
P-value RMSEA <= 0.05	0.350	0.000
Robust RMSEA		NA
90 Percent confidence interval - lower		NA
90 Percent confidence interval - upper		NA

## Standardized Root Mean Square Residual:

SRMR	0.041	0.041
------	-------	-------

## Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

## Latent Variables:

Estimate	Std.Err	z-value	P(> z )	Std.lv
----------	---------	---------	---------	--------



Std.all

pres =~

FFA_1	1.000				0.597
0.597					
FFA_2	0.964	0.049	19.674	0.000	0.576
0.576					
FFA_3	0.934	0.046	20.172	0.000	0.558
0.558					
FFA_5	1.259	0.053	23.871	0.000	0.752
0.752					
FFA_7	1.289	0.051	25.172	0.000	0.770
0.770					

acc =~

FFA_4	1.000				0.677
0.677					
FFA_6	1.059	0.031	34.081	0.000	0.717
0.717					
FFA_8	0.871	0.038	23.190	0.000	0.590
0.590					
FFA_9	1.049	0.033	31.978	0.000	0.711
0.711					
FFA_10	1.077	0.034	31.636	0.000	0.730
0.730					
FFA_11	1.080	0.035	30.534	0.000	0.731
0.731					
FFA_12	1.058	0.035	30.596	0.000	0.717
0.717					
FFA_14	0.889	0.037	23.840	0.000	0.602
0.602					

Covariances:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
pres ~~					
acc	0.373	0.020	18.824	0.000	0.922
0.922					

Intercepts:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
.FFA_1	0.000				0.000
0.000					
.FFA_2	0.000				0.000
0.000					

.FFA_3	0.000	0.000
0.000		
.FFA_5	0.000	0.000
0.000		
.FFA_7	0.000	0.000
0.000		
.FFA_4	0.000	0.000
0.000		
.FFA_6	0.000	0.000
0.000		
.FFA_8	0.000	0.000
0.000		
.FFA_9	0.000	0.000
0.000		
.FFA_10	0.000	0.000
0.000		
.FFA_11	0.000	0.000
0.000		
.FFA_12	0.000	0.000
0.000		
.FFA_14	0.000	0.000
0.000		
pres	0.000	0.000
0.000		
acc	0.000	0.000
0.000		

## Thresholds:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
FFA_1 t1	-1.474	0.060	-24.664	0.000	-1.474
-1.474					
FFA_1 t2	-0.621	0.042	-14.662	0.000	-0.621
-0.621					
FFA_1 t3	0.679	0.043	15.814	0.000	0.679
0.679					
FFA_2 t1	-1.118	0.050	-22.425	0.000	-1.118
-1.118					
FFA_2 t2	-0.012	0.039	-0.315	0.753	-0.012
-0.012					
FFA_2 t3	1.091	0.049	22.132	0.000	1.091
1.091					
FFA_3 t1	-1.047	0.048	-21.626	0.000	-1.047
-1.047					

FFA_3 t2	0.082	0.040	2.076	0.038	0.082
0.082					
FFA_3 t3	1.282	0.054	23.814	0.000	1.282
1.282					
FFA_5 t1	-1.466	0.059	-24.647	0.000	-1.466
-1.466					
FFA_5 t2	-0.536	0.042	-12.885	0.000	-0.536
-0.536					
FFA_5 t3	0.803	0.044	18.073	0.000	0.803
0.803					
FFA_7 t1	-1.397	0.057	-24.427	0.000	-1.397
-1.397					
FFA_7 t2	-0.454	0.041	-11.091	0.000	-0.454
-0.454					
FFA_7 t3	0.881	0.046	19.341	0.000	0.881
0.881					
FFA_4 t1	-1.527	0.062	-24.752	0.000	-1.527
-1.527					
FFA_4 t2	-0.530	0.042	-12.762	0.000	-0.530
-0.530					
FFA_4 t3	0.664	0.043	15.512	0.000	0.664
0.664					
FFA_6 t1	-1.551	0.063	-24.771	0.000	-1.551
-1.551					
FFA_6 t2	-0.435	0.041	-10.657	0.000	-0.435
-0.435					
FFA_6 t3	0.856	0.045	18.941	0.000	0.856
0.856					
FFA_8 t1	-1.711	0.070	-24.583	0.000	-1.711
-1.711					
FFA_8 t2	-0.516	0.041	-12.453	0.000	-0.516
-0.516					
FFA_8 t3	0.885	0.046	19.397	0.000	0.885
0.885					
FFA_9 t1	-1.384	0.057	-24.373	0.000	-1.384
-1.384					
FFA_9 t2	-0.328	0.040	-8.162	0.000	-0.328
-0.328					
FFA_9 t3	0.977	0.047	20.728	0.000	0.977
0.977					
FFA_10 t1	-1.346	0.056	-24.195	0.000	-1.346
-1.346					
FFA_10 t2	-0.347	0.040	-8.600	0.000	-0.347
-0.347					

FFA_10 t3	0.941	0.047	20.237	0.000	0.941
0.941					
FFA_11 t1	-1.417	0.058	-24.502	0.000	-1.417
-1.417					
FFA_11 t2	-0.368	0.040	-9.099	0.000	-0.368
-0.368					
FFA_11 t3	0.918	0.046	19.904	0.000	0.918
0.918					
FFA_12 t1	-1.181	0.051	-23.029	0.000	-1.181
-1.181					
FFA_12 t2	-0.070	0.039	-1.761	0.078	-0.070
-0.070					
FFA_12 t3	1.123	0.050	22.473	0.000	1.123
1.123					
FFA_14 t1	-1.304	0.054	-23.960	0.000	-1.304
-1.304					
FFA_14 t2	-0.167	0.040	-4.213	0.000	-0.167
-0.167					
FFA_14 t3	1.105	0.050	22.279	0.000	1.105
1.105					

## Variances:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
.FFA_1	0.643				0.643
0.643					
.FFA_2	0.668				0.668
0.668					
.FFA_3	0.689				0.689
0.689					
.FFA_5	0.435				0.435
0.435					
.FFA_7	0.407				0.407
0.407					
.FFA_4	0.541				0.541
0.541					
.FFA_6	0.486				0.486
0.486					
.FFA_8	0.652				0.652
0.652					
.FFA_9	0.495				0.495
0.495					
.FFA_10	0.467				0.467
0.467					

.FFA_11	0.465				0.465
0.465					
.FFA_12	0.486				0.486
0.486					
.FFA_14	0.637				0.637
0.637					
pres	0.357	0.027	13.130	0.000	1.000
1.000					
acc	0.459	0.026	17.743	0.000	1.000
1.000					

Scales y\*:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
FFA_1	1.000				1.000
1.000					
FFA_2	1.000				1.000
1.000					
FFA_3	1.000				1.000
1.000					
FFA_5	1.000				1.000
1.000					
FFA_7	1.000				1.000
1.000					
FFA_4	1.000				1.000
1.000					
FFA_6	1.000				1.000
1.000					
FFA_8	1.000				1.000
1.000					
FFA_9	1.000				1.000
1.000					
FFA_10	1.000				1.000
1.000					
FFA_11	1.000				1.000
1.000					
FFA_12	1.000				1.000
1.000					
FFA_14	1.000				1.000
1.000					

## 9.3.2 1F model

```
ffa_mod_1F <- 'm =~ FFA_1 + FFA_2 + FFA_3 + FFA_5 + FFA_7 + FFA_4 + FFA_6'

ffa_cfa_1F <- lavaan::cfa(ffa_mod_1F, data = ffa_items2, ordered = TRUE)
#ffa_cfa <- lavaan::cfa(ffa_mod, data = ffa_items2)

ffa_cfa_1F
```

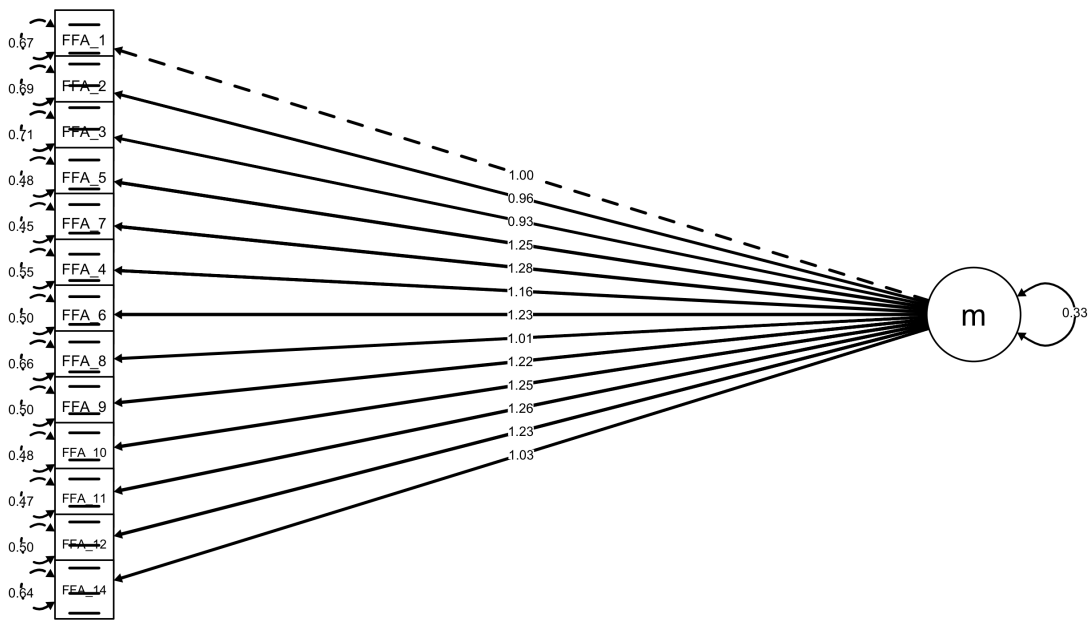
lavaan 0.6-12 ended normally after 23 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	52
Number of observations	1010

Model Test User Model:

	Standard	Robust
Test Statistic	265.438	482.961
Degrees of freedom	65	65
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.559
Shift parameter		8.327
simple second-order correction		

```
semPaths(ffa_cfa_1F, what = "est", intercepts = FALSE,
         rotation = 4, edge.color = 1, fade = FALSE,
         edge.label.cex = .5, edge.width = .3)
```



```
summary(ffa_cfa_1F, standardized = TRUE, fit.measures = TRUE)
```

lavaan 0.6-12 ended normally after 23 iterations

Estimator	DWLS
Optimization method	NLMINB
Number of model parameters	52
Number of observations	1010

Model Test User Model:

	Standard	Robust
Test Statistic	265.438	482.961
Degrees of freedom	65	65
P-value (Chi-square)	0.000	0.000
Scaling correction factor		0.559
Shift parameter		8.327
simple second-order correction		

Model Test Baseline Model:

Test statistic	23657.526	8990.511
Degrees of freedom	78	78
P-value	0.000	0.000

Scaling correction factor	2.646
---------------------------	-------

## User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.991	0.953
Tucker-Lewis Index (TLI)	0.990	0.944
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

## Root Mean Square Error of Approximation:

RMSEA	0.055	0.080
90 Percent confidence interval - lower	0.048	0.073
90 Percent confidence interval - upper	0.062	0.087
P-value RMSEA <= 0.05	0.100	0.000
Robust RMSEA		NA
90 Percent confidence interval - lower		NA
90 Percent confidence interval - upper		NA

## Standardized Root Mean Square Residual:

SRMR	0.044	0.044
------	-------	-------

## Parameter Estimates:

Standard errors	Robust.sem
Information	Expected
Information saturated (h1) model	Unstructured

## Latent Variables:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
m =~					
FFA_1	1.000				0.577
0.577					
FFA_2	0.961	0.049	19.627	0.000	0.555
0.555					
FFA_3	0.932	0.046	20.112	0.000	0.538
0.538					
FFA_5	1.253	0.052	24.005	0.000	0.724
0.724					
FFA_7	1.281	0.051	25.358	0.000	0.740



0.740

FFA_4	1.162	0.053	22.115	0.000	0.671
-------	-------	-------	--------	-------	-------

0.671

FFA_6	1.230	0.052	23.441	0.000	0.710
-------	-------	-------	--------	-------	-------

0.710

FFA_8	1.013	0.050	20.431	0.000	0.585
-------	-------	-------	--------	-------	-------

0.585

FFA_9	1.220	0.052	23.583	0.000	0.704
-------	-------	-------	--------	-------	-------

0.704

FFA_10	1.251	0.050	24.817	0.000	0.722
--------	-------	-------	--------	-------	-------

0.722

FFA_11	1.255	0.053	23.683	0.000	0.725
--------	-------	-------	--------	-------	-------

0.725

FFA_12	1.231	0.050	24.444	0.000	0.711
--------	-------	-------	--------	-------	-------

0.711

FFA_14	1.035	0.051	20.441	0.000	0.597
--------	-------	-------	--------	-------	-------

0.597

Intercepts:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
--	----------	---------	---------	---------	--------

Std.all

.FFA_1	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_2	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_3	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_5	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_7	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_4	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_6	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_8	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_9	0.000				0.000
--------	-------	--	--	--	-------

0.000

.FFA_10	0.000				0.000
---------	-------	--	--	--	-------

0.000

.FFA_11	0.000				0.000
---------	-------	--	--	--	-------

0.000

.FFA_12	0.000				0.000
---------	-------	--	--	--	-------

0.000

.FFA\_14

0.000

0.000

0.000

m

0.000

0.000

0.000

## Thresholds:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
FFA_1 t1	-1.474	0.060	-24.664	0.000	-1.474
-1.474					
FFA_1 t2	-0.621	0.042	-14.662	0.000	-0.621
-0.621					
FFA_1 t3	0.679	0.043	15.814	0.000	0.679
0.679					
FFA_2 t1	-1.118	0.050	-22.425	0.000	-1.118
-1.118					
FFA_2 t2	-0.012	0.039	-0.315	0.753	-0.012
-0.012					
FFA_2 t3	1.091	0.049	22.132	0.000	1.091
1.091					
FFA_3 t1	-1.047	0.048	-21.626	0.000	-1.047
-1.047					
FFA_3 t2	0.082	0.040	2.076	0.038	0.082
0.082					
FFA_3 t3	1.282	0.054	23.814	0.000	1.282
1.282					
FFA_5 t1	-1.466	0.059	-24.647	0.000	-1.466
-1.466					
FFA_5 t2	-0.536	0.042	-12.885	0.000	-0.536
-0.536					
FFA_5 t3	0.803	0.044	18.073	0.000	0.803
0.803					
FFA_7 t1	-1.397	0.057	-24.427	0.000	-1.397
-1.397					
FFA_7 t2	-0.454	0.041	-11.091	0.000	-0.454
-0.454					
FFA_7 t3	0.881	0.046	19.341	0.000	0.881
0.881					
FFA_4 t1	-1.527	0.062	-24.752	0.000	-1.527
-1.527					
FFA_4 t2	-0.530	0.042	-12.762	0.000	-0.530
-0.530					
FFA_4 t3	0.664	0.043	15.512	0.000	0.664

0.664					
FFA_6 t1	-1.551	0.063	-24.771	0.000	-1.551
-1.551					
FFA_6 t2	-0.435	0.041	-10.657	0.000	-0.435
-0.435					
FFA_6 t3	0.856	0.045	18.941	0.000	0.856
0.856					
FFA_8 t1	-1.711	0.070	-24.583	0.000	-1.711
-1.711					
FFA_8 t2	-0.516	0.041	-12.453	0.000	-0.516
-0.516					
FFA_8 t3	0.885	0.046	19.397	0.000	0.885
0.885					
FFA_9 t1	-1.384	0.057	-24.373	0.000	-1.384
-1.384					
FFA_9 t2	-0.328	0.040	-8.162	0.000	-0.328
-0.328					
FFA_9 t3	0.977	0.047	20.728	0.000	0.977
0.977					
FFA_10 t1	-1.346	0.056	-24.195	0.000	-1.346
-1.346					
FFA_10 t2	-0.347	0.040	-8.600	0.000	-0.347
-0.347					
FFA_10 t3	0.941	0.047	20.237	0.000	0.941
0.941					
FFA_11 t1	-1.417	0.058	-24.502	0.000	-1.417
-1.417					
FFA_11 t2	-0.368	0.040	-9.099	0.000	-0.368
-0.368					
FFA_11 t3	0.918	0.046	19.904	0.000	0.918
0.918					
FFA_12 t1	-1.181	0.051	-23.029	0.000	-1.181
-1.181					
FFA_12 t2	-0.070	0.039	-1.761	0.078	-0.070
-0.070					
FFA_12 t3	1.123	0.050	22.473	0.000	1.123
1.123					
FFA_14 t1	-1.304	0.054	-23.960	0.000	-1.304
-1.304					
FFA_14 t2	-0.167	0.040	-4.213	0.000	-0.167
-0.167					
FFA_14 t3	1.105	0.050	22.279	0.000	1.105
1.105					

## Variances:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
.FFA_1	0.667				0.667
0.667					
.FFA_2	0.692				0.692
0.692					
.FFA_3	0.710				0.710
0.710					
.FFA_5	0.476				0.476
0.476					
.FFA_7	0.453				0.453
0.453					
.FFA_4	0.550				0.550
0.550					
.FFA_6	0.496				0.496
0.496					
.FFA_8	0.658				0.658
0.658					
.FFA_9	0.504				0.504
0.504					
.FFA_10	0.478				0.478
0.478					
.FFA_11	0.474				0.474
0.474					
.FFA_12	0.495				0.495
0.495					
.FFA_14	0.643				0.643
0.643					
m	0.333	0.026	12.752	0.000	1.000
1.000					

## Scales y\*:

	Estimate	Std.Err	z-value	P(> z )	Std.lv
Std.all					
FFA_1	1.000				1.000
1.000					
FFA_2	1.000				1.000
1.000					
FFA_3	1.000				1.000
1.000					
FFA_5	1.000				1.000
1.000					
FFA_7	1.000				1.000

1.000		
FFA_4	1.000	1.000
1.000		
FFA_6	1.000	1.000
1.000		
FFA_8	1.000	1.000
1.000		
FFA_9	1.000	1.000
1.000		
FFA_10	1.000	1.000
1.000		
FFA_11	1.000	1.000
1.000		
FFA_12	1.000	1.000
1.000		
FFA_14	1.000	1.000
1.000		

### 9.3.3 Conclusion

The CFA seems to speak in favor of the 2F solution.