Documentation of Analyses

25 Juli 2016

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# Setup

The following contains the documentation of all analysis conducted for the manuscript entitled **title title XX** and submitted to **PLoS One** at xxxx-xx-xx.  
We primarily used the free and open source software R (R Core Team, 2014). Multilevel confirmatory factor analysis and multilevel structural equation models were estimated with MPlus 7.1 (L. K. Muthén & Muthén, 2012) using the R package MplusAutomation (Hallquist & Wiley, 2016) as a R leverage.

# Datawrangling

Experimental conditions and rotations of the booklets resulted in 12 different rawdata files. The following code junks descripe their import, joining, recoding and reshaping.

## Import

raw\_erf\_r1 <- read.table("data/erf\_r1/daten.csv", sep = ";", header = T)  
raw\_erf\_r2 <- read.table("data/erf\_r2/daten.csv", sep = ";", header = T)  
raw\_erf\_r3 <- read.table("data/erf\_r3/daten.csv", sep = ";", header = T)  
raw\_erf\_r4 <- read.table("data/erf\_r4/daten.csv", sep = ";", header = T)  
raw\_exp\_r1 <- read.table("data/exp\_r1/daten.csv", sep = ";", header = T)  
raw\_exp\_r2 <- read.table("data/exp\_r2/daten.csv", sep = ";", header = T)  
raw\_exp\_r3 <- read.table("data/exp\_r3/daten.csv", sep = ";", header = T)  
raw\_exp\_r4 <- read.table("data/exp\_r4/daten.csv", sep = ";", header = T)  
raw\_wis\_r1 <- read.table("data/wis\_r1/daten.csv", sep = ";", header = T)  
raw\_wis\_r2 <- read.table("data/wis\_r2/daten.csv", sep = ";", header = T)  
raw\_wis\_r3 <- read.table("data/wis\_r3/daten.csv", sep = ";", header = T)  
raw\_wis\_r4 <- read.table("data/wis\_r4/daten.csv", sep = ";", header = T)

## Joining

rawdata <- full\_join(raw\_erf\_r1,  
 full\_join(raw\_erf\_r2,  
 full\_join(raw\_erf\_r3,  
 full\_join(raw\_erf\_r4,  
 full\_join(raw\_exp\_r1,  
 full\_join(raw\_exp\_r2,  
 full\_join(raw\_exp\_r3,  
 full\_join(raw\_exp\_r4,  
 full\_join(raw\_wis\_r1,  
 full\_join(raw\_wis\_r2,  
 full\_join(raw\_wis\_r3, raw\_wis\_r4)))))))))))

## Recoding

#names(rawdata%>%select(ends\_with("\_ip")))  
  
rawdata <- rawdata%>%  
 mutate(source = as.factor(substr(rawdata$Pseudonym, 1,3)),  
 te\_01\_np = tx\_02\_np\_t1, ## CAEB recoding and renaming: te = texture, vr = variability  
 te\_02\_np = tx\_04\_np\_t1,   
 te\_03\_np = 8 - tx\_05\_ip\_t1,  
 te\_04\_np = tx\_06\_np\_t1,   
 te\_05\_np = tx\_07\_np\_t1,   
 te\_06\_np = tx\_08\_np\_t1,   
 te\_07\_np = tx\_09\_np\_t1,   
 te\_08\_np = tx\_10\_np\_t1,   
 te\_09\_np = 8 - tx\_11\_ip\_t1,  
 te\_10\_np = tx\_12\_np\_t1,   
   
 vr\_01\_np = va\_01\_np\_t1,   
 vr\_02\_np = 8 - va\_02\_ip\_t1,   
 vr\_03\_np = 8 - va\_03\_ip\_t1,   
 vr\_04\_np = 8 - va\_04\_ip\_t1,   
 vr\_05\_np = va\_05\_np\_t1,   
 vr\_06\_np = 8 - tx\_13\_ip\_t1,   
 vr\_07\_np = 8 - va\_06\_ip\_t1,   
   
 si\_03\_np = 7 - si\_03\_ip, ## Study interest  
 si\_04\_np = 7 - si\_04\_ip,  
 si\_06\_np = 7 - si\_06\_ip,  
   
 sk\_03\_np = 5 - sk\_03\_ip, ## Self-Concept  
   
   
 ## Worked out examples text  
 dd\_we\_ie\_05\_np = 7 - dd\_we\_ie\_05\_ip, ## Interest-Enjoy  
 dd\_we\_tp\_02\_np = 5 - dd\_we\_tp\_02\_ip, ## Theory-Praxis-Relation  
 dd\_we\_tp\_04\_np = dd\_we\_tp\_04\_ip,  
 dd\_we\_tp\_06\_np = dd\_we\_tp\_06\_ip,   
 dd\_we\_ko\_02\_np = 5 - dd\_we\_ko\_02\_ip, ## Koherence  
 dd\_we\_ko\_04\_np = 5 - dd\_we\_ko\_04\_ip,   
  
 ## CTM text  
 dd\_cm\_ie\_05\_np = 7 - dd\_cm\_ie\_05\_ip, ## Interest-Enjoy  
 dd\_cm\_tp\_02\_np = 5 - dd\_cm\_tp\_02\_ip, ## Theory-Praxis-Relation  
 dd\_cm\_tp\_04\_np = dd\_cm\_tp\_04\_ip,  
 dd\_cm\_tp\_06\_np = dd\_cm\_tp\_06\_ip,   
 dd\_cm\_ko\_02\_np = 5 - dd\_cm\_ko\_02\_ip, ## Koherence  
 dd\_cm\_ko\_04\_np = 5 - dd\_cm\_ko\_04\_ip,   
   
 ## BFLP text  
 ed\_bp\_ie\_05\_np = 7 - ed\_bp\_ie\_05\_ip, ## Interest-Enjoy  
 ed\_bp\_tp\_02\_np = 5 - ed\_bp\_tp\_02\_ip, ## Theory-Praxis-Relation  
 ed\_bp\_tp\_04\_np = ed\_bp\_tp\_04\_ip,  
 ed\_bp\_tp\_06\_np = ed\_bp\_tp\_06\_ip,   
 ed\_bp\_ko\_02\_np = 5 - ed\_bp\_ko\_02\_ip, ## Koherence  
 ed\_bp\_ko\_04\_np = 5 - ed\_bp\_ko\_04\_ip,   
   
 ## CLassroom size text  
 ed\_cs\_ie\_05\_np = 7 - ed\_cs\_ie\_05\_ip, ## Interest-Enjoy  
 ed\_cs\_tp\_02\_np = 5 - ed\_cs\_tp\_02\_ip, ## Theory-Praxis-Relation  
 ed\_cs\_tp\_04\_np = ed\_cs\_tp\_04\_ip,  
 ed\_cs\_tp\_06\_np = ed\_cs\_tp\_06\_ip,   
 ed\_cs\_ko\_02\_np = 5 - ed\_cs\_ko\_02\_ip, ## Koherence  
 ed\_cs\_ko\_04\_np = 5 - ed\_cs\_ko\_04\_ip,  
   
   
 ## D-Index FREE  
 di\_01\_np = po\_01\_np - 0.5\*(ab\_01\_np + re\_01\_np),  
 di\_02\_np = po\_02\_np - 0.5\*(ab\_02\_np + re\_02\_np),  
 di\_03\_np = po\_03\_np - 0.5\*(ab\_03\_np + re\_03\_np),  
 di\_04\_np = po\_04\_np - 0.5\*(ab\_04\_np + re\_04\_np),  
 di\_05\_np = po\_05\_np - 0.5\*(ab\_05\_np + re\_05\_np),  
 di\_06\_np = po\_06\_np - 0.5\*(ab\_06\_np + re\_06\_np),  
 di\_07\_np = po\_07\_np - 0.5\*(ab\_07\_np + re\_07\_np),  
 di\_08\_np = po\_08\_np - 0.5\*(ab\_08\_np + re\_08\_np),  
 di\_09\_np = po\_09\_np - 0.5\*(ab\_09\_np + re\_09\_np),  
 di\_10\_np = po\_10\_np - 0.5\*(ab\_10\_np + re\_10\_np),  
 di\_11\_np = po\_11\_np - 0.5\*(ab\_11\_np + re\_11\_np),  
 di\_12\_np = po\_12\_np - 0.5\*(ab\_12\_np + re\_12\_np),  
 di\_13\_np = po\_13\_np - 0.5\*(ab\_13\_np + re\_13\_np))  
  
  
# Reject inverse coded original item  
rawdata\_np <- tbl\_df(rawdata%>%  
 select(-ends\_with("\_ip"),  
 -starts\_with("tx\_"),  
 -starts\_with("va\_")  
 )  
 )  
  
  
  
  
# Create dummy variables (sum constrasts) for source  
rawdata\_np$I\_exp <- ifelse(rawdata\_np$source == "exp", 1,  
 ifelse(rawdata\_np$source == "erf", -1,0))  
  
  
rawdata\_np$I\_wis <- ifelse(rawdata\_np$source == "wis", 1,  
 ifelse(rawdata\_np$source == "erf", -1,0))

## Reshape to long form & group mean centering

As MPlus requires the so called "long format" of multilevel data we reshaped our join to that format. Also we needed to group mean center the level-1 (within-person level) predictors, to make sure that the random intercept are interpretable as person specific means of the dependend variable.

rawdata\_long\_np <- rawdata\_np%>%  
 mutate(source = substr(Pseudonym, 1,3),  
 rotation = substr(Pseudonym, 5,6))%>%  
 gather(withinitem, value, starts\_with("dd\_") , starts\_with("ed\_"))%>%  
 mutate(paradigm = substr(withinitem, 1,2),  
 topic = substr(withinitem, 4,5),  
 withinitem2 = as.factor(substr(withinitem, 7,14)))%>%  
 select(-withinitem)%>%  
 select(-starts\_with("dd"))%>%  
 select(-starts\_with("ed"))%>%  
 spread(withinitem2, value)%>%  
 group\_by(Pseudonym)%>%  
 mutate(tr\_01\_pc = tr\_01\_np - mean(tr\_01\_np, na.rm = TRUE), ## Group Mean Centering  
 tr\_02\_pc = tr\_02\_np - mean(tr\_02\_np, na.rm = TRUE),  
 tr\_03\_pc = tr\_03\_np - mean(tr\_03\_np, na.rm = TRUE),  
 tr\_04\_pc = tr\_04\_np - mean(tr\_04\_np, na.rm = TRUE),  
 ke\_01\_pc = ke\_01\_np - mean(ke\_01\_np, na.rm = TRUE),  
 cl\_01\_pc = cl\_01\_np - mean(cl\_01\_np, na.rm = TRUE),  
 cl\_02\_pc = cl\_02\_np - mean(cl\_02\_np, na.rm = TRUE),  
 cl\_03\_pc = cl\_03\_np - mean(cl\_03\_np, na.rm = TRUE),  
 ie\_01\_pc = ie\_01\_np - mean(ie\_01\_np, na.rm = TRUE),  
 ie\_02\_pc = ie\_02\_np - mean(ie\_02\_np, na.rm = TRUE),  
 ie\_03\_pc = ie\_03\_np - mean(ie\_03\_np, na.rm = TRUE),  
 ie\_04\_pc = ie\_04\_np - mean(ie\_04\_np, na.rm = TRUE),  
 ie\_05\_pc = ie\_05\_np - mean(ie\_05\_np, na.rm = TRUE),  
 ko\_01\_pc = ko\_01\_np - mean(ko\_01\_np, na.rm = TRUE),  
 ko\_02\_pc = ko\_02\_np - mean(ko\_02\_np, na.rm = TRUE),  
 ko\_03\_pc = ko\_03\_np - mean(ko\_03\_np, na.rm = TRUE))%>%  
 ungroup()  
  
  
rawdata\_long\_np$IDnum <- as.numeric(as.factor(rawdata\_long\_np$Pseudonym)) ## Create numeric Person identifier for MPlus  
rawdata\_long\_np$topic <- factor(rawdata\_long\_np$topic, levels=c("we", "cm", "bp", "cs")) ## Reorder Factor Levels  
rawdata\_long\_np$sourcenum <- as.numeric(as.factor(rawdata\_long\_np$source)) ## Convert Factor Levels to numeric factor for MPlus)

# Instruments

The questionaire contained between-person level variables (asked every student teacher once) as well as within-person level variables (asked each student teacher once per topic). The follwing code describes the (multi-level) confirmatory factor analyses (MCFA), which allowed us to also report estimations of reliability using McDonalds ω (Dunn, Baguley, & Brunsden, 2013). Therefore we first specified so called "independent clusters model of confirmatory factor analysis (ICM-CFA)". If the model fit was lower then our criteria, we estimated measurement error covariances (within on factor and choosen by modification indices) freely.  
Details about multi-level confirmatory factor analyses are given in the methods section of the corresponding article.

## Print functions

## Define a print function for MPlus-Output  
fpf\_mp <- function(x){   
   
 fm\_tmp <- readModels(as.character(x))  
   
 return(sprintf(  
 "χ² = %s, \_df\_ = %s,  
 CFI = %s, TLI = %s,   
 RMSEA = %s, SRMR~within~ = %s,  
 SRMR~between~ = %s",  
 round(fm\_tmp$summaries$ChiSqM\_Value,3),   
 fm\_tmp$summaries$ChiSqM\_DF,  
 round(fm\_tmp$summaries$CFI,3),  
 round(fm\_tmp$summaries$TLI,3),  
 round(fm\_tmp$summaries$RMSEA\_Estimate,3),  
 round(fm\_tmp$summaries$SRMR.Within,3),  
 round(fm\_tmp$summaries$SRMR.Between,3)  
 )  
 )  
}  
  
## Define a reliability print function for within person variables  
library(dplyr)  
rpf\_wv <- function(x){   
   
 reldat <- rawdata\_long\_np%>%  
 select(starts\_with(as.character(x)), topic)%>%  
 select(-ends\_with("pc"))%>%  
 group\_by(topic)%>%  
 do(data.frame(alpha = MBESS::ci.reliability(data.frame(select(., starts\_with(as.character(x)))))))  
   
   
 return(sprintf(  
 "%s < ω < %s (union of 95%%CI[%s, %s])",  
 round(min(reldat$alpha.est), 2),  
 round(max(reldat$alpha.est), 2),  
 round(min(reldat$alpha.ci.lower), 2),  
 round(max(reldat$alpha.ci.upper), 2)  
 )  
 )  
}  
  
## Define a print function for lavaan-Output ##############################  
fpf\_la <- function(x){   
  
 fm\_tmp <- fitmeasures(x)  
   
 return(sprintf(  
 "χ² = %s, \_df\_ = %s, CFI = %s, TLI = %s, RMSEA = %s, SRMR = %s",  
 round(fm\_tmp[c("chisq")],3),   
 fm\_tmp[c("df")],  
 round(fm\_tmp[c("cfi")],3),  
 round(fm\_tmp[c("tli")],3),  
 round(fm\_tmp[c("rmsea")],3),  
 round(fm\_tmp[c("srmr")],3)  
 )  
 )  
}  
  
  
## Define a reliability print function for between person variables  
  
rpf\_bv <- function(x){   
   
 reldat <- rawdata\_np%>%  
 select(starts\_with(as.character(x)))%>%  
 select(-ends\_with("pc"))  
 relinfo <- MBESS::ci.reliability(data.frame(select(reldat, starts\_with(as.character(x)))))  
   
   
 return(sprintf(  
 "ω = %s, 95%%CI[%s, %s])",  
 round(relinfo$est, 2),  
 round(relinfo$ci.lower, 2),  
 round(relinfo$ci.upper, 2)  
 )  
 )  
}

## Perceived Theory-Practice-Integration

### MCFA

rawdata\_long\_np$IDnum <- as.numeric(as.factor(rawdata\_long\_np$Pseudonym))  
  
MCFA\_tp\_unres <- mplusObject(  
   
 TITLE = "MCFA\_\_tp\_unres",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np;  
 CLUSTER = IDnum;",  
   
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
   
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;",  
   
 OUTPUT = "Standardized;",  
   
 rdata = rawdata\_long\_np)  
  
MCFA\_tp\_unres\_fit <- mplusModeler(MCFA\_tp\_unres, "MCFA\_tp\_unres.dat", run = 1)

### Fit Indices of the MCFA:

χ² = 58.674, *df* = 18, CFI = 0.974, TLI = 0.956, RMSEA = 0.04, SRMRwithin = 0.024, SRMRbetween = 0.062

### Reliability estimates:

0.74 < ω < 0.78 (union of 95%CI[0.7, 0.81])

## Theory-Specific Relativism

library(MplusAutomation)  
MCFA\_tr\_unres <- mplusObject(  
   
 TITLE = "MCFA\_tr\_unres",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tr\_01\_np tr\_02\_np tr\_03\_np tr\_04\_np;  
 CLUSTER = IDnum;",  
   
   
 MODEL = "%WITHIN%  
 trW BY tr\_01\_np tr\_02\_np tr\_03\_np tr\_04\_np;  
   
 %BETWEEN%  
 trB BY tr\_01\_np tr\_02\_np tr\_03\_np tr\_04\_np;  
 TR\_03\_NP WITH TR\_01\_NP;  
 TR\_04\_NP WITH TR\_02\_NP; ",   
   
 OUTPUT = "Standardized; MODINDICES",  
   
 rdata = rawdata\_long\_np)  
  
MCFA\_tr\_unres\_fit <- mplusModeler(MCFA\_tr\_unres, "MCFA\_tr\_unres.dat", run = 1)

### Fit Indices of the MCFA:

χ² = 5.11, *df* = 2, CFI = 0.996, TLI = 0.974, RMSEA = 0.033, SRMRwithin = 0.021, SRMRbetween = 0.012

### Reliability estimates:

0.68 < ω < 0.75 (union of 95%CI[0.62, 0.79])

## Koherence with the topic

As a ICM-MCFA resulted in bad fit indices for the SRMR at the between level we fit a model, where the random intercepts only covaried.

library(MplusAutomation)  
MCFA\_ko\_within <- mplusObject(  
   
 TITLE = "MCFA\_ko\_within",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = ko\_01\_np ko\_02\_np ko\_03\_np;  
   
 CLUSTER = IDnum;",  
   
 MODEL = "%WITHIN%  
 koW BY ko\_01\_np(1)  
 ko\_02\_np(1)  
 ko\_03\_np(1);  
  
 %Between%  
 ko\_01\_np WITH ko\_02\_np ko\_03\_np;  
 ko\_02\_np WITH ko\_03\_np; ",   
   
 OUTPUT = "Standardized; Modindices",  
 rdata = rawdata\_long\_np)  
  
MCFA\_ko\_within\_fit <- mplusModeler(MCFA\_ko\_within, "MCFA\_ko\_within.dat", run = 1)

### Fit Indices of the MCFA:

χ² = 9.162, *df* = 1, CFI = 994, TLI = 962, RMSEA = .075, SRMRwithin = .005, SRMRbetween = .065

### Reliability estimates:

reldat\_ko <- rawdata\_long\_np%>%  
 select(starts\_with(as.character("ko\_")), topic)%>%  
 select(-ends\_with("pc"), -ko\_04\_np)%>%  
 group\_by(topic)%>%  
 do(data.frame(alpha = MBESS::ci.reliability(data.frame(select(., starts\_with(as.character("ko")))))))  
   
   
sprintf(  
 "%s < ω < %s (union of .95CI[%s,%s])",  
 round(min(reldat\_ko$alpha.est), 2),  
 round(max(reldat\_ko$alpha.est), 2),  
 round(min(reldat\_ko$alpha.ci.lower), 2),  
 round(max(reldat\_ko$alpha.ci.upper), 2)  
   
 )

[1] "0.83 < ω < 0.89 (union of .95CI[0.8,0.91])"

## Knowledge about the topic

We assed knowledge about the topic with an single item.

## Epistemic development

di.cfa.model <- "di =~ di\_01\_np + di\_02\_np + di\_03\_np + di\_04\_np + di\_05\_np + di\_06\_np + di\_07\_np +   
 di\_08\_np + di\_09\_np + di\_10\_np + di\_11\_np + di\_12\_np + di\_13\_np  
 di\_04\_np ~~ di\_05\_np  
 di\_03\_np ~~ di\_06\_np"  
di.cfa.fitted <- cfa(di.cfa.model, data = rawdata\_np)

### Fit Indices of the CFA:

χ² = 98.757, *df* = 63, CFI = 0.93, TLI = 0.913, RMSEA = 0.043, SRMR = 0.047

### Reliability estimates:

ω = 0.75, 95%CI[0.71, 0.79])

## Epistemic beliefs inventory

ebi.cfa.model <- "abs =~ stab\_a\_27 + stab\_a\_41 + rech\_a\_03 + rech\_a\_06 + rech\_a\_10 + komp\_a\_07 +  
 komp\_a\_20 + komp\_a\_42 + komp\_a\_39 + quel\_a\_08 + quel\_a\_11 + quel\_a\_35  
 rel =~ stab\_r\_04 + stab\_r\_18 + stab\_r\_23 + stab\_r\_21 + rech\_r\_17 + rech\_r\_33 + komp\_r\_22 + komp\_r\_30 + komp\_r\_43 + quel\_r\_09 + quel\_r\_34  
  
 stab =~ stab\_a\_27 + stab\_a\_41 + stab\_r\_04 + stab\_r\_18  
 rech =~ rech\_a\_03 + rech\_a\_06 + rech\_a\_10 + rech\_r\_17 + rech\_r\_33  
 komp =~ komp\_a\_07 + komp\_a\_20 + komp\_a\_42 + komp\_a\_39 + komp\_r\_22 + komp\_r\_30 +   
 komp\_r\_43  
 quel =~ quel\_a\_08 + quel\_a\_11 + quel\_a\_35 + quel\_r\_09 + quel\_r\_34  
  
 quel\_a\_11 ~~ quel\_a\_35  
 stab\_r\_04 ~~ stab\_r\_23  
 rech\_r\_17 ~~ rech\_r\_33 "   
  
  
  
ebi.cfa.fitted <- cfa(ebi.cfa.model, data = rawdata)

### Fit Indices of the CFA:

χ² = 275.316, *df* = 191, CFI = 0.93, TLI = 0.907, RMSEA = 0.038, SRMR = 0.045

### Reliability estimates:

* Absolutism: ω = 0.73, 95%CI[0.69, 0.77])
* Relativism: ω = 0.74, 95%CI[0.7, 0.78])

## Connotative aspect of epistemic beliefs

caeb.cfa.model <- " tex =~ te\_01\_np + te\_02\_np + te\_03\_np + te\_04\_np + te\_05\_np + te\_06\_np +   
 te\_07\_np + te\_08\_np + te\_09\_np + te\_10\_np  
 var =~ vr\_01\_np + vr\_02\_np + vr\_03\_np + vr\_04\_np + vr\_05\_np + vr\_06\_np +   
 vr\_07\_np  
 te\_06\_np ~~ te\_10\_np  
 te\_05\_np ~~ te\_08\_np  
 vr\_02\_np ~~ vr\_04\_np  
 te\_03\_np ~~ vr\_03\_np   
 vr\_04\_np ~~ vr\_07\_np   
 te\_06\_np ~~ te\_07\_np "  
  
  
caeb.cfa.fitted <- cfa(caeb.cfa.model, data = rawdata\_np)

### Fit Indices of the CFA:

χ² = 243.305, *df* = 112, CFI = 0.901, TLI = 0.88, RMSEA = 0.06, SRMR = 0.062

### Reliability estimates:

* Variability: ω = 0.63, 95%CI[0.56, 0.68])
* Texture: ω = 0.8, 95%CI[0.76, 0.83])

## Muenster epistemic truthworthiness inventory

meti.cfa.model <- "me =~ me\_01\_np + me\_02\_np + me\_03\_np + me\_04\_np + me\_05\_np + me\_06\_np  
 mi =~ mi\_01\_np + mi\_02\_np + mi\_03\_np + mi\_04\_np  
 mb =~ mb\_01\_np + mb\_02\_np + mb\_03\_np + mb\_04\_np  
  
 mi\_01\_np ~~ mi\_02\_np  
 mb\_01\_np ~~ mb\_02\_np  
 mi\_03\_np ~~ mi\_04\_np  
 mb\_03\_np ~~ mb\_04\_np"  
  
meti.cfa.fitted <- cfa(meti.cfa.model, data = rawdata\_np)

### Fit Indices of the CFA:

χ² = 192.95, *df* = 70, CFI = 0.956, TLI = 0.942, RMSEA = 0.072, SRMR = 0.054

### Reliability estimates:

* Expertise: ω = 0.88, 95%CI[0.86, 0.9])
* Integrity: ω = 0.84, 95%CI[0.81, 0.87])
* Benevolence: ω = 0.87, 95%CI[0.84, 0.89])

# Results

This sections provides the code and output of the analyses we conducted to investigate our hypotheses. Note that the heading the same than in the corresponding article.

## Confirmatory Factor Analysis

### M1: MCFA with level-variant measurement models

MCFA\_tp\_unres <- mplusObject(  
   
 TITLE = "MCFA\_\_tp\_unres",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np;  
   
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np  
 tp\_02\_np  
 tp\_03\_np  
 tp\_04\_np  
 tp\_05\_np  
 tp\_06\_np;  
   
   
 %BETWEEN%  
 TPB BY tp\_01\_np  
 tp\_02\_np  
 tp\_03\_np  
 tp\_04\_np  
 tp\_05\_np  
 tp\_06\_np;",  
 OUTPUT = "Standardized;",  
 rdata = rawdata\_long\_np)  
  
MCFA\_tp\_unres\_fit <- mplusModeler(MCFA\_tp\_unres, "MCFA\_tp\_unres.dat", run = 1)

* The fitindices of M1 were χ² = 58.674, *df* = 18, CFI = 0.974, TLI = 0.956, RMSEA = 0.04, SRMRwithin = 0.024, SRMRbetween = 0.062
* An estimation of ICC(1)-coeffients resulted in a range of 0.21 and 0.33.

### M2: MCFA with level-invariant measurement models

# Mplusmodell  
MCFA\_tp\_res <- mplusObject(  
   
 TITLE = "MCFA\_tp\_res",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np;  
   
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np(01)  
 tp\_02\_np(02)  
 tp\_03\_np(03)  
 tp\_04\_np(04)  
 tp\_05\_np(05)  
 tp\_06\_np(06);  
   
   
 %BETWEEN%  
 TPB BY tp\_01\_np(01)  
 tp\_02\_np(02)  
 tp\_03\_np(03)  
 tp\_04\_np(04)  
 tp\_05\_np(05)  
 tp\_06\_np(06);",  
   
 OUTPUT = "Standardized Modindices(5);",  
   
 rdata = rawdata\_long\_np)  
  
MCFA\_tp\_res\_fit <- mplusModeler(MCFA\_tp\_res, "MCFA\_tp\_res.dat", run = 1)

* The fitindices of M2 were χ² = 93.76, *df* = 23, CFI = 0.955, TLI = 0.941, RMSEA = 0.046, SRMRwithin = 0.037, SRMRbetween = 0.12)
* A modelcomparison test resulted in:

compareModels(readModels("MCFA\_tp\_unres.out"), readModels("MCFA\_tp\_res.out"), diffTest = T, show = "summaries")

##   
## ==============  
##   
## Mplus model comparison  
## ----------------------  
##   
## Reading model: MCFA\_tp\_unres.out   
## ------  
## Model 1: MCFA\_tp\_unres.out   
## Reading model: MCFA\_tp\_res.out   
## Model 2: MCFA\_tp\_res.out   
## ------  
##   
## Model Summary Comparison  
## ------------------------  
##   
## m1 m2   
## Title MCFA\_\_tp\_unres MCFA\_tp\_res  
## Observations 1443 1443   
## Estimator MLR MLR   
## Parameters 30 25   
## LL -9368.382 -9389.009   
## AIC 18796.764 18828.017   
## BIC 18954.998 18959.879   
## ChiSqM\_Value 58.674 93.76   
## ChiSqM\_DF 18 23   
## CFI 0.974 0.955   
## TLI 0.956 0.941   
## RMSEA\_Estimate 0.04 0.046   
##   
## MLR Chi-Square Difference Test for Nested Models Based on Loglikelihood  
## -----------------------------------------------------------------------  
##   
## Difference Test Scaling Correction: 1.2534   
## Chi-square difference: 32.9137   
## Diff degrees of freedom: 5   
## P-value: 0   
##   
## Note: The chi-square difference test assumes that these models are nested.  
## It is up to you to verify this assumption.  
##   
## MLR Chi-Square Difference test for nested models  
## --------------------------------------------  
##   
## Difference Test Scaling Correction: 1.25316   
## Chi-square difference: 32.9217   
## Diff degrees of freedom: 5   
## P-value: 0   
##   
## Note: The chi-square difference test assumes that these models are nested.  
## It is up to you to verify this assumption.  
##   
## ==============

* The ICC of the latent variable was 0.36

## Predictive Effects of Source (H1)

### M3: Multi-Group MCFA Model

### MGMCFA Modell \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
  
MGMCFA\_tp\_strong <- mplusObject(  
   
 TITLE = "MGMCFA\_tp\_strong",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np;  
 GROUPING IS sourcenum (1 = erf 2 = exp 3 = wis);  
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
   
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
   
 tp\_06\_np@0 ;",  
  
 OUTPUT = "Standardized MODINDICES(5);",  
 rdata = rawdata\_long\_np)  
  
MGMCFA\_tp\_strong\_fit <- mplusModeler(MGMCFA\_tp\_strong, "MGMCFA\_tp\_strong.dat", run = 1)

* The fitindices of M3 were: χ² = 166.282, *df* = 87, CFI = 0.954, TLI = 0.952, RMSEA = 0.044, SRMRwithin = 0.042, SRMRbetween = 0.131

### M4: MIMIC Model with source indicator variables as predictors

# Dummyvariables for MIMIC Model   
rawdata\_long\_np$I\_exp <- ifelse(rawdata\_long\_np$source == "exp", 1, 0)  
rawdata\_long\_np$I\_wis <- ifelse(rawdata\_long\_np$source == "wis", 1, 0)  
  
  
### MIMIC\_pred\_source Modell \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
  
MIMIC\_pred\_source <- mplusObject(  
   
 TITLE = "MIMIC\_pred\_source",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np I\_exp I\_wis;  
  
 BETWEEN = I\_exp I\_wis;  
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
  
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 tp\_06\_np@0;  
 TPB ON I\_exp I\_wis;",  
   
 OUTPUT = "Standardized MODINDICES(5);",  
   
 rdata = rawdata\_long\_np)  
  
MIMIC\_pred\_source\_fit <- mplusModeler(MIMIC\_pred\_source, "MIMIC\_pred\_source.dat", run = 1)

* The fitindices of M4 were: χ² = 85.644, *df* = 29, CFI = 0.966, TLI = 0.951, RMSEA = 0.037, SRMRwithin = 0.025, SRMRbetween = 0.066

## Predictive Effects of epistemic beliefs (H2)

### M5: Predictive Effects of D-Index

rawdata\_long\_np <-  
 rawdata\_long\_np%>%  
 mutate(di\_gc = scale(rowMeans(data.frame(di\_01\_np, di\_02\_np, di\_03\_np, di\_04\_np, di\_05\_np,   
 di\_06\_np, di\_07\_np, di\_08\_np, di\_09\_np, di\_10\_np,  
 di\_11\_np, di\_12\_np, di\_13\_np), na.rm = T), scale = F),  
 tr\_pc = rowMeans(data.frame(tr\_01\_pc, tr\_02\_pc, tr\_03\_pc, tr\_04\_pc), na.rm = T),  
 di\_gc = ifelse(scale(di\_gc) > 3.29, NA, ifelse(scale(di\_gc) < -3.29, NA, di\_gc)), ## removing outliers  
 tr\_pc = ifelse(scale(tr\_pc) > 3.29, NA, ifelse(scale(tr\_pc) < -3.29, NA, tr\_pc)), ## in the way we preregistered  
 di\_gc\_exp = di\_gc\*I\_exp,  
 di\_gc\_wis = di\_gc\*I\_wis)  
  
  
### MGMCFA Modell \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
  
MIMIC\_pred\_di\_man <- mplusObject(  
   
 TITLE = "MIMIC\_pred\_di\_man",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np  
 tr\_pc  
 di\_gc di\_gc\_exp di\_gc\_wis I\_exp I\_wis;  
  
 WITHIN = tr\_pc;  
 BETWEEN = di\_gc di\_gc\_exp di\_gc\_wis I\_exp I\_wis;  
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 TPW ON tr\_pc;  
  
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 tp\_05\_np@0;  
 TPB ON di\_gc di\_gc\_exp di\_gc\_wis I\_exp I\_wis;",  
   
 OUTPUT = "Standardized MODINDICES(5);",  
   
 rdata = rawdata\_long\_np)  
  
MIMIC\_pred\_di\_man\_fit <- mplusModeler(MIMIC\_pred\_di\_man, "MIMIC\_pred\_di\_man.dat", run = 1)

* The fitindices of M5 were: χ² = 112.246, *df* = 49, CFI = 0.968, TLI = 0.956, RMSEA = 0.03, SRMRwithin = 0.024, SRMRbetween = 0.055
* The standardized predictive effects of M5 were:

MIMIC\_pred\_di\_man\_results <- readModels("MIMIC\_pred\_di\_man.out")

Reading model: MIMIC\_pred\_di\_man.out

pander::pander(MIMIC\_pred\_di\_man\_results$parameters$stdyx.standardized%>% filter(grepl("ON", paramHeader)))

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| paramHeader | param | est | se | est\_se | pval | BetweenWithin |
| TPW.ON | TR\_PC | -0.432 | 0.029 | -14.85 | 0 | Within |
| TPB.ON | DI\_GC | -0.037 | 0.111 | -0.33 | 0.742 | Between |
| TPB.ON | DI\_GC\_EXP | 0.138 | 0.098 | 1.405 | 0.16 | Between |
| TPB.ON | DI\_GC\_WIS | 0.15 | 0.079 | 1.909 | 0.056 | Between |
| TPB.ON | I\_EXP | 0.027 | 0.075 | 0.363 | 0.717 | Between |
| TPB.ON | I\_WIS | 0.284 | 0.073 | 3.894 | 0 | Between |

### M6: Predictive Effects of EBI

rawdata\_long\_np <-  
 rawdata\_long\_np%>%  
 mutate(abs\_gc = scale(rowMeans(data.frame(stab\_a\_27, stab\_a\_41, rech\_a\_03, rech\_a\_06, rech\_a\_10, komp\_a\_07,  
 komp\_a\_20, komp\_a\_42, komp\_a\_39, quel\_a\_08, quel\_a\_11, quel\_a\_35), na.rm = T),  
 scale = F),  
 rel\_gc = scale(rowMeans(data.frame(stab\_r\_04, stab\_r\_18, stab\_r\_23, stab\_r\_21, rech\_r\_17, rech\_r\_33,   
 komp\_r\_22, komp\_r\_30, komp\_r\_43, quel\_r\_09, quel\_r\_34), na.rm = T),   
 scale = F),  
 abs\_gc = ifelse(scale(abs\_gc) > 3.29, NA, ifelse(scale(abs\_gc) < -3.29, NA, abs\_gc)), ## removing outliers  
 rel\_gc = ifelse(scale(rel\_gc) > 3.29, NA, ifelse(scale(rel\_gc) < -3.29, NA, rel\_gc)), ## in the way we preregistered  
 abs\_gc\_exp = abs\_gc\*I\_exp,  
 rel\_gc\_exp = rel\_gc\*I\_exp,  
 abs\_gc\_wis = abs\_gc\*I\_wis,  
 rel\_gc\_wis = rel\_gc\*I\_wis)  
  
### MIMIC\_pred\_ebi\_man Modell \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
  
MIMIC\_pred\_ebi\_man <- mplusObject(  
   
 TITLE = "MIMIC\_pred\_ebi\_man",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np  
 tr\_pc  
 abs\_gc rel\_gc abs\_gc\_exp rel\_gc\_exp abs\_gc\_wis rel\_gc\_wis   
 I\_exp I\_wis;  
  
 WITHIN = tr\_pc;  
 BETWEEN = abs\_gc rel\_gc abs\_gc\_exp rel\_gc\_exp abs\_gc\_wis rel\_gc\_wis  
 I\_exp I\_wis;  
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 TPW ON tr\_pc;  
  
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 tp\_05\_np@0;  
 TPB ON abs\_gc rel\_gc abs\_gc\_exp rel\_gc\_exp abs\_gc\_wis rel\_gc\_wis   
 I\_exp I\_wis;  
   
   
 ",  
 OUTPUT = "Standardized MODINDICES(5);",  
 rdata = rawdata\_long\_np)  
  
MIMIC\_pred\_ebi\_man\_fit <- mplusModeler(MIMIC\_pred\_ebi\_man, "MIMIC\_pred\_ebi\_man.dat", run = 1)

* The fitindices of M6 were: χ² = 148.461, *df* = 64, CFI = 0.957, TLI = 0.944, RMSEA = 0.03, SRMRwithin = 0.024, SRMRbetween = 0.057
* The standardized predictive effects of M6 were:

MIMIC\_pred\_ebi\_man\_results <- readModels("MIMIC\_pred\_ebi\_man.out")

Reading model: MIMIC\_pred\_ebi\_man.out

pander::pander(MIMIC\_pred\_ebi\_man\_results$parameters$stdyx.standardized%>% filter(grepl("ON", paramHeader)))

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| paramHeader | param | est | se | est\_se | pval | BetweenWithin |
| TPW.ON | TR\_PC | -0.42 | 0.029 | -14.31 | 0 | Within |
| TPB.ON | ABS\_GC | 0.467 | 0.119 | 3.936 | 0 | Between |
| TPB.ON | REL\_GC | 0.138 | 0.105 | 1.31 | 0.19 | Between |
| TPB.ON | ABS\_GC\_EXP | -0.132 | 0.098 | -1.355 | 0.175 | Between |
| TPB.ON | REL\_GC\_EXP | 0.05 | 0.088 | 0.569 | 0.569 | Between |
| TPB.ON | ABS\_GC\_WIS | -0.234 | 0.098 | -2.392 | 0.017 | Between |
| TPB.ON | REL\_GC\_WIS | -0.067 | 0.085 | -0.782 | 0.434 | Between |
| TPB.ON | I\_EXP | 0.055 | 0.072 | 0.76 | 0.448 | Between |
| TPB.ON | I\_WIS | 0.28 | 0.073 | 3.829 | 0 | Between |

## Confounders of Predictive Effects of epistemic beliefs

### M7: Confounders of Predictive Effects D-Index (H3)

### Generate arithemtic means of scales \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
rawdata\_long\_np <- rawdata\_long\_np%>%  
 mutate(cl\_pc = rowMeans(data.frame(cl\_01\_pc, cl\_02\_pc, cl\_03\_pc), na.rm = T),  
 ko\_pc = rowMeans(data.frame(ko\_01\_pc, ko\_02\_pc, ko\_03\_pc), na.rm = T),  
 me\_np = rowMeans(data.frame(me\_01\_np, me\_02\_np, me\_03\_np, me\_04\_np, me\_05\_np, me\_06\_np), na.rm = T),  
 mi\_np = rowMeans(data.frame(mi\_01\_np, mi\_02\_np, mi\_03\_np, mi\_04\_np), na.rm = T),  
 mb\_np = rowMeans(data.frame(mb\_01\_np, mb\_02\_np, mb\_03\_np, mb\_04\_np), na.rm = T),  
 ko\_pc = ifelse(scale(ko\_pc) > 3.29, NA,ifelse(scale(ko\_pc) < -3.29, NA, ko\_pc)),  
 me\_np = ifelse(scale(me\_np) > 3.29, NA,ifelse(scale(me\_np) < -3.29, NA, me\_np)),  
 mi\_np = ifelse(scale(mi\_np) > 3.29, NA,ifelse(scale(mi\_np) < -3.29, NA, mi\_np)),  
 mb\_np = ifelse(scale(mb\_np) > 3.29, NA,ifelse(scale(mb\_np) < -3.29, NA, mb\_np)))  
  
  
  
### MIMIC\_conf\_di\_man Modell \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
  
MIMIC\_conf\_di\_man <- mplusObject(  
   
 TITLE = "MIMIC\_conf\_di\_man",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np  
 tr\_pc ke\_01\_pc ko\_pc   
 di\_gc di\_gc\_exp di\_gc\_wis I\_exp I\_wis me\_np mi\_np mb\_np;  
  
 WITHIN = tr\_pc ke\_01\_pc ko\_pc;  
 BETWEEN = di\_gc di\_gc\_exp di\_gc\_wis I\_exp I\_wis me\_np mi\_np mb\_np;  
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
  
 TPW ON tr\_pc ke\_01\_pc ko\_pc ;  
  
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 tp\_05\_np@0;  
 TPB ON di\_gc di\_gc\_exp di\_gc\_wis I\_exp I\_wis me\_np mi\_np mb\_np; ",  
   
 OUTPUT = "Standardized MODINDICES(5);",  
   
 rdata = rawdata\_long\_np)  
  
MIMIC\_conf\_di\_man\_fit <- mplusModeler(MIMIC\_conf\_di\_man, "MIMIC\_conf\_di\_man.dat", run = 1)

* The fitindices of M7 were: χ² = 148.954, *df* = 74, CFI = 0.967, TLI = 0.957, RMSEA = 0.027, SRMRwithin = 0.026, SRMRbetween = 0.043
* The standardized predictive effects of M7 were:

MIMIC\_conf\_di\_man\_results <- readModels("MIMIC\_conf\_di\_man.out")

Reading model: MIMIC\_conf\_di\_man.out

pander::pander(MIMIC\_conf\_di\_man\_results$parameters$stdyx.standardized%>% filter(grepl("ON", paramHeader)))

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| paramHeader | param | est | se | est\_se | pval | BetweenWithin |
| TPW.ON | TR\_PC | -0.216 | 0.031 | -6.951 | 0 | Within |
| TPW.ON | KE\_01\_PC | 0.071 | 0.033 | 2.172 | 0.03 | Within |
| TPW.ON | KO\_PC | 0.441 | 0.031 | 14.24 | 0 | Within |
| TPB.ON | DI\_GC | -0.066 | 0.107 | -0.613 | 0.54 | Between |
| TPB.ON | DI\_GC\_EXP | 0.112 | 0.091 | 1.232 | 0.218 | Between |
| TPB.ON | DI\_GC\_WIS | 0.116 | 0.077 | 1.499 | 0.134 | Between |
| TPB.ON | I\_EXP | 0.05 | 0.068 | 0.741 | 0.459 | Between |
| TPB.ON | I\_WIS | 0.217 | 0.071 | 3.065 | 0.002 | Between |
| TPB.ON | ME\_NP | -0.397 | 0.075 | -5.317 | 0 | Between |
| TPB.ON | MI\_NP | -0.027 | 0.074 | -0.372 | 0.71 | Between |
| TPB.ON | MB\_NP | -0.126 | 0.075 | -1.684 | 0.092 | Between |

### M8: Confounders of Predictive Effects EBI (H3)

### MIMIC\_conf\_ebi\_man Modell \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
  
MIMIC\_conf\_ebi\_man <- mplusObject(  
   
 TITLE = "MIMIC\_conf\_ebi\_man",  
   
 ANALYSIS = "TYPE = TWOLEVEL;",  
   
 VARIABLE = "USEVARIABLES = tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np   
 tp\_05\_np tp\_06\_np  
 tr\_pc ke\_01\_pc ko\_pc   
 abs\_gc rel\_gc abs\_gc\_exp rel\_gc\_exp abs\_gc\_wis rel\_gc\_wis  
 I\_exp I\_wis me\_np mi\_np mb\_np;  
  
 WITHIN = tr\_pc ke\_01\_pc ko\_pc;  
 BETWEEN = abs\_gc rel\_gc abs\_gc\_exp rel\_gc\_exp abs\_gc\_wis rel\_gc\_wis  
 I\_exp I\_wis me\_np mi\_np mb\_np;  
 CLUSTER = IDnum;",  
   
  
 MODEL = "%WITHIN%  
 TPW BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
  
 TPW ON tr\_pc ke\_01\_pc ko\_pc ;  
  
 %BETWEEN%  
 TPB BY tp\_01\_np tp\_02\_np tp\_03\_np tp\_04\_np tp\_05\_np tp\_06\_np;  
 tp\_05\_np@0;  
 TPB ON abs\_gc rel\_gc abs\_gc\_exp rel\_gc\_exp abs\_gc\_wis rel\_gc\_wis  
 I\_exp I\_wis me\_np mi\_np mb\_np;",  
   
 OUTPUT = "Standardized MODINDICES(5);",  
   
 rdata = rawdata\_long\_np)  
  
MIMIC\_conf\_ebi\_man\_fit <- mplusModeler(MIMIC\_conf\_ebi\_man, "MIMIC\_conf\_ebi\_man.dat", run = 1)

* The fitindices of M8 were: χ² = 181.307, *df* = 89, CFI = 0.96, TLI = 0.948, RMSEA = 0.027, SRMRwithin = 0.026, SRMRbetween = 0.047
* The standardized predictive effects of M8 were:

MIMIC\_conf\_ebi\_man\_results <- readModels("MIMIC\_conf\_ebi\_man.out")

Reading model: MIMIC\_conf\_ebi\_man.out

pander::pander(MIMIC\_conf\_ebi\_man\_results$parameters$stdyx.standardized%>% filter(grepl("ON", paramHeader)))

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| paramHeader | param | est | se | est\_se | pval | BetweenWithin |
| TPW.ON | TR\_PC | -0.206 | 0.031 | -6.605 | 0 | Within |
| TPW.ON | KE\_01\_PC | 0.073 | 0.033 | 2.221 | 0.026 | Within |
| TPW.ON | KO\_PC | 0.449 | 0.031 | 14.61 | 0 | Within |
| TPB.ON | ABS\_GC | 0.38 | 0.102 | 3.714 | 0 | Between |
| TPB.ON | REL\_GC | 0.153 | 0.092 | 1.667 | 0.096 | Between |
| TPB.ON | ABS\_GC\_EXP | -0.138 | 0.082 | -1.683 | 0.092 | Between |
| TPB.ON | REL\_GC\_EXP | 0.04 | 0.079 | 0.504 | 0.614 | Between |
| TPB.ON | ABS\_GC\_WIS | -0.188 | 0.086 | -2.172 | 0.03 | Between |
| TPB.ON | REL\_GC\_WIS | -0.062 | 0.073 | -0.841 | 0.4 | Between |
| TPB.ON | I\_EXP | 0.06 | 0.068 | 0.891 | 0.373 | Between |
| TPB.ON | I\_WIS | 0.206 | 0.072 | 2.869 | 0.004 | Between |
| TPB.ON | ME\_NP | -0.403 | 0.069 | -5.829 | 0 | Between |
| TPB.ON | MI\_NP | -0.054 | 0.072 | -0.756 | 0.45 | Between |
| TPB.ON | MB\_NP | -0.092 | 0.073 | -1.265 | 0.206 | Between |

# Literature

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