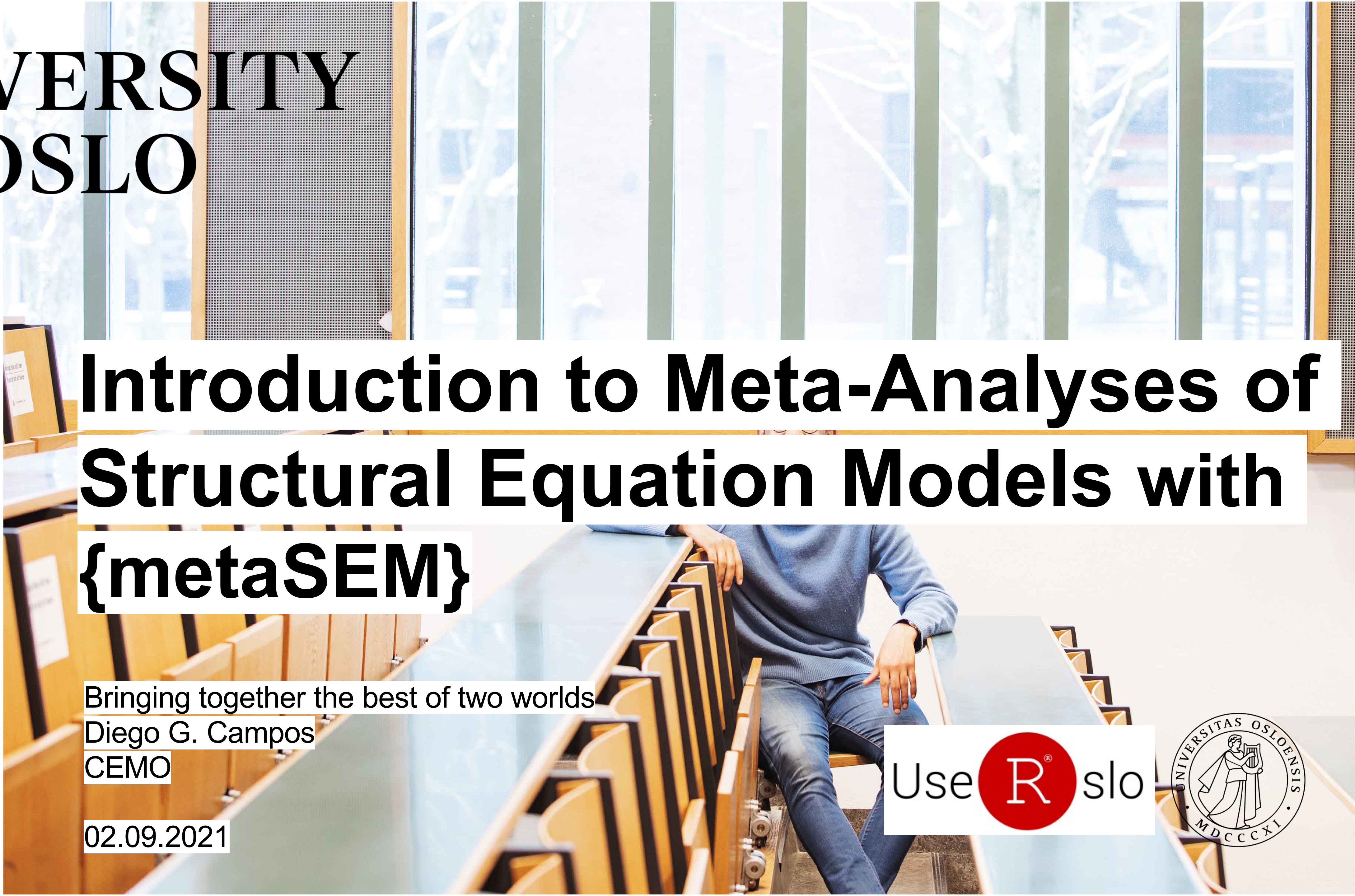
UNIVERSITY OF OSLO



Introduction to Meta-Analyses of Structural Equation Models with {metaSEM}

Bringing together the best of two worlds

Diego G. Campos
CEMO

02.09.2021

UseR!Oslo

MASEM Concepts

Meta-Analysis

Interest in the average effects

Interest in differences between studies

Photo by [Kimberly Farmer] on [Unsplash]

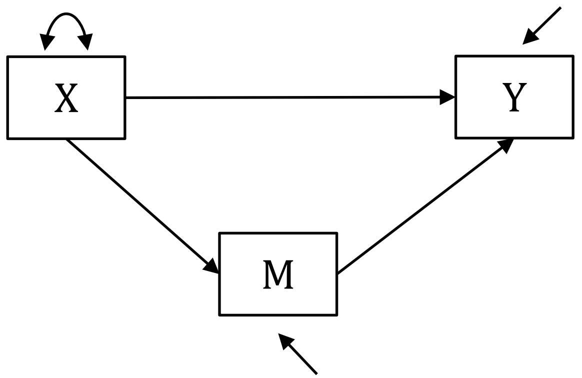
UseRslo

UiO : CEMO – Centre for Educational Measurement
University of Oslo

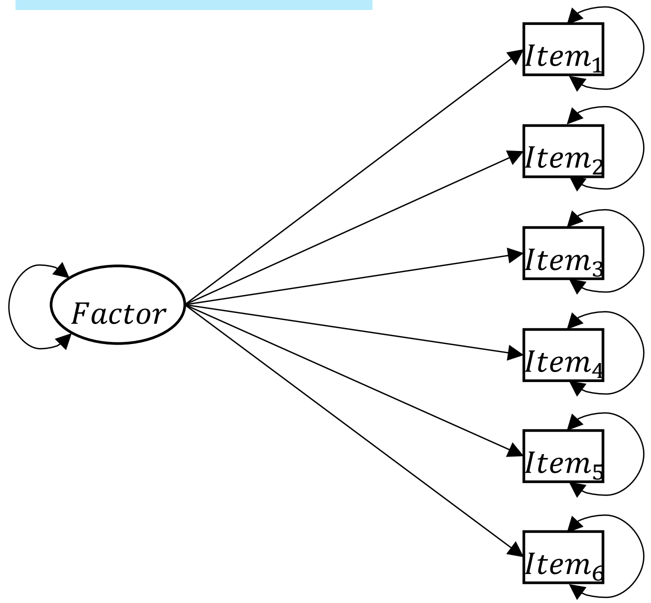
MASEM Concepts

Structural Equational Modeling

Path Model



Factor model



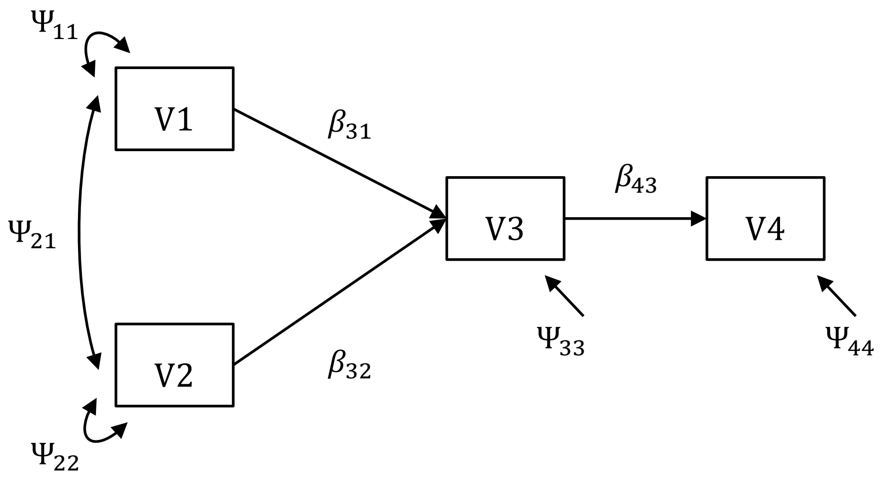
No raw data needed

MASEM Concepts

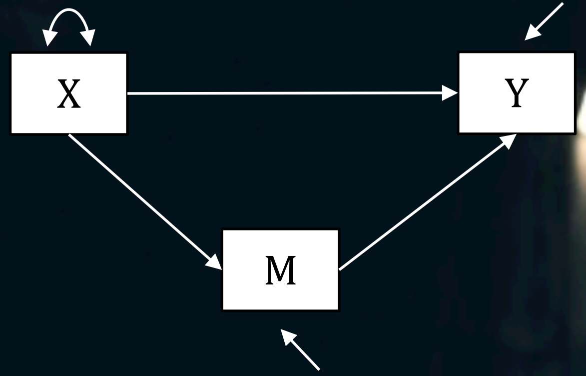
Structural Equational Modeling

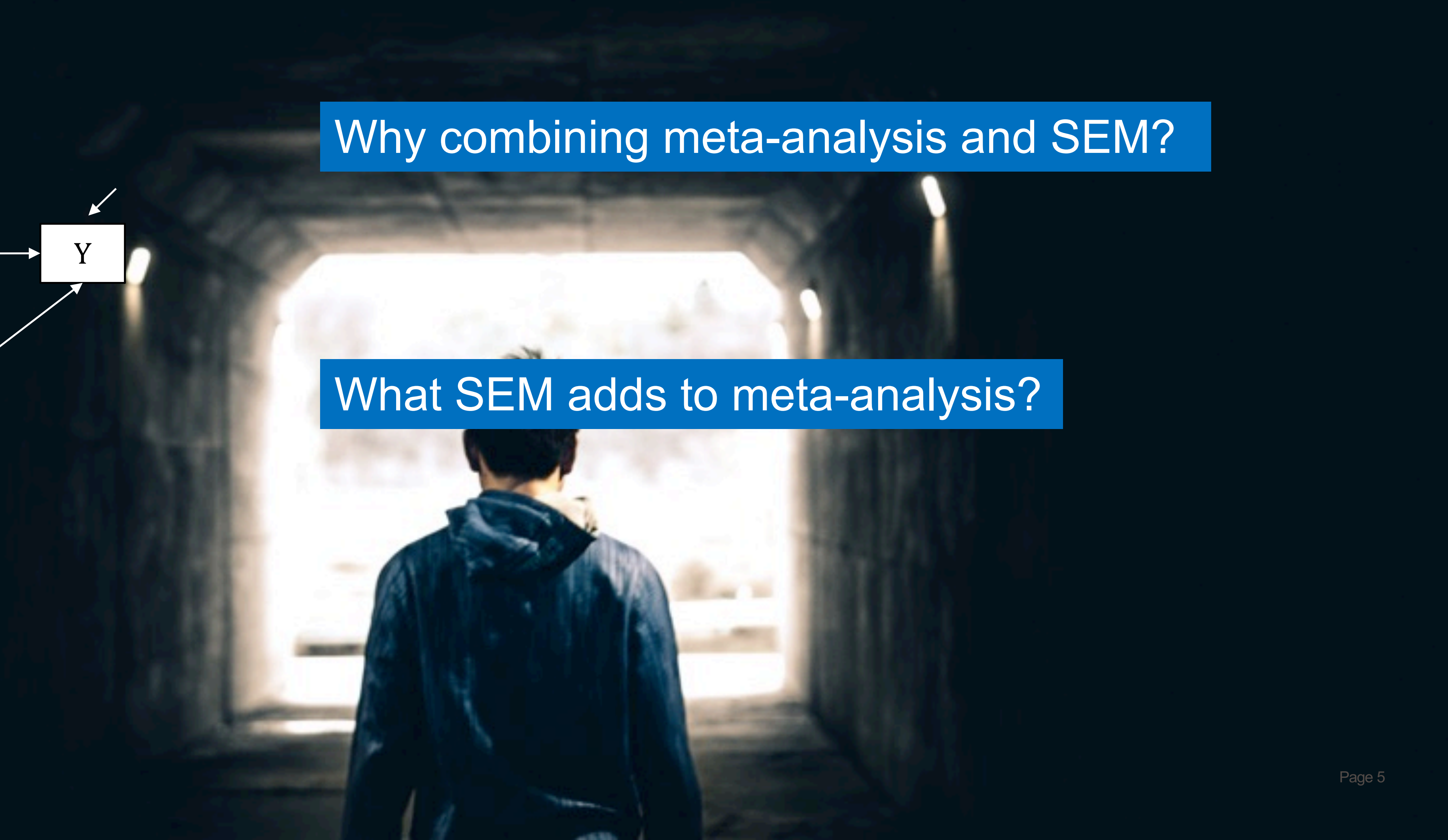
- The covariance matrix between the observed variables is modeled as a function of SEM parameters.

V1	V2	V3	V4
1.00			
ρ_{21}	1.00		
ρ_{31}	ρ_{32}	1.00	
ρ_{41}	ρ_{42}	ρ_{43}	1.00



Why MASEM?

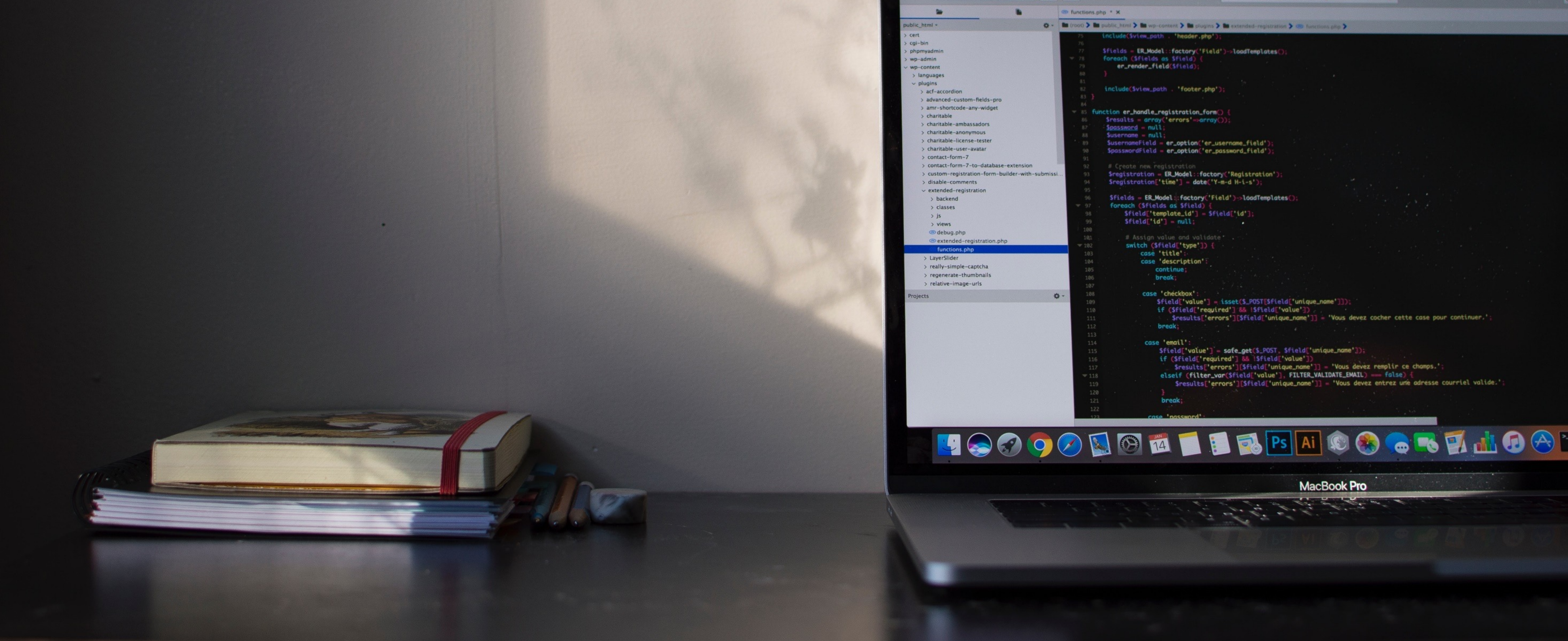




Why combining meta-analysis and SEM?

What SEM adds to meta-analysis?

MASEM Example

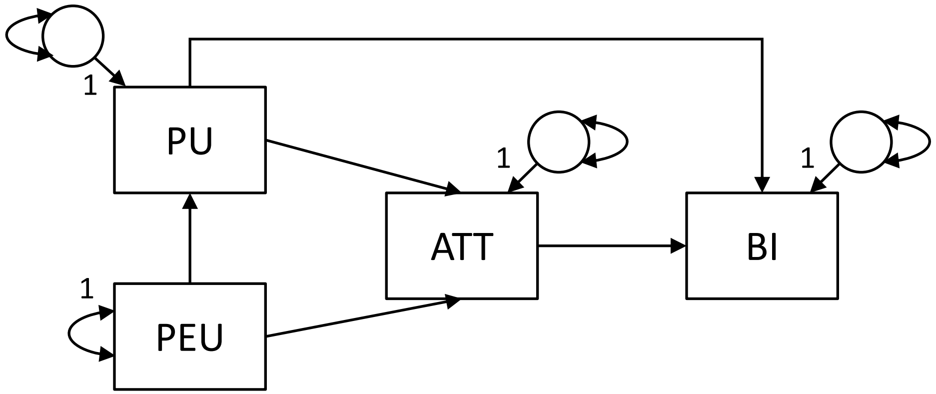


Technology Acceptance Model (TAM)

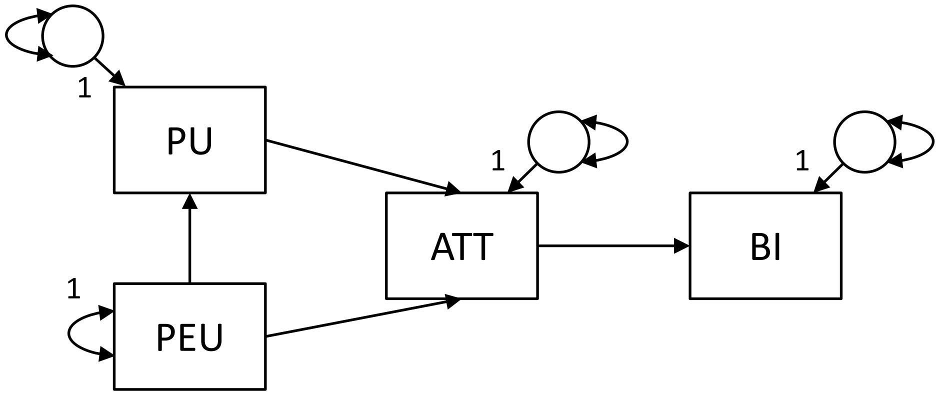
A Model Explaining Teachers’ Intentions to Use Technology

Variables

- BI: Intentions to use technology, ATT: Attitudes toward technology
- PEU: Perceived ease of use, PU: Perceived usefulness



Model 1



Model 2

Scherer, R., & Teo, T. (2019). Unpacking teachers’ intentions to integrate technology: A meta-analysis. Educational Research Review, 27, 90-109. https://doi.org/10.1016/j.edurev.2019.03.001

Technology Acceptance Model (TAM)

Meta-analytic data set based on teacher samples

Data set

- 50 studies with independent samples
- 4 variables
- 300 correlations
- 50 correlation matrices
- Pre- and in-service teacher samples

Main RQs

1. **Model evaluation:** To what extent does the TAM represent the teacher data across samples?
2. **Model comparison:** To what extent does a direct effect exist?

Scherer, R., & Teo, T. (2019). Unpacking teachers' intentions to integrate technology: A meta-analysis. Educational Research Review, 27, 90-109. https://doi.org/10.1016/j.edurev.2019.03.001

R

Reading the Data

PU	PEU	ATT	BI
1.00			
ρ_{21}	1.00		
ρ_{31}	ρ_{32}	1.00	
ρ_{41}	ρ_{42}	ρ_{43}	1.00

	A	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH
1	StudyID	Sample size	PU-PU	PU-PEOU	PEOU	PU-ATT	PEOU-ATT	ATT-ATT	PU-BI	PEOU-BI	ATT-BI	BI-BI
2	217	446	1	0,61	1	0,6776	0,5138	1	0,599184	0,449892	0,860328	1
3	247	88	1	0,661	1	0,59	0,584	1	0,75	0,746	0,684	1
4	281	271	1	0,89	1	0,423	0,187	1	0,374	0,82	0,512	1
5	289	234	1	0,5	1	0,64	0,55	1	0,55	0,48	0,59	1
6	311	29	1	0,512	1	0,461	0,754	1	0,364	0,669	0,595	1
7	320	313	1	0,279	1	0,63	0,873	1	0,319	0,441	0,505	1
8	332A	169	1	0,68	1	0,68	0,73	1	0,34	0,3	0,3	1
9	332B	170	1	0,4	1	0,56	0,43	1	0,23	0,32	0,36	1
10	335A	151	1	0,329	1	0,565	0,349	1	0,523	0,327	0,462	1

1. A list of correlation/covariance matrices.
2. A vector of sample size.

Understanding and Exploring your Data

Test for positive definitiveness.

```r
# PD check
pd_check <- is.pd(TAMu$data)
sum(!is.na(pd_check))
```

```
## [1] 50
```

```r
pd_check
```

```
##  Okazaki & Renda dos Santos (2012)
##                               TRUE
##                        Wong (2015)
##                               TRUE
```

Explore your data.

```r
# Some description of the studies
# Available studies per correlation
pattern.na(TAMu$data, show.na=FALSE)
```

```
    PU PEU ATT BI
PU  50  50  50 50
PEU 50  50  50 50
ATT 50  50  50 50
BI  50  50  50 50
```

```r
# Available sample sizes per correlation
pattern.n(TAMu$data, TAMu$n)
```

```
       PU   PEU   ATT    BI
PU  14918 14918 14918 14918
PEU 14918 14918 14918 14918
ATT 14918 14918 14918 14918
BI  14918 14918 14918 14918
```

Stage 1: Pooling Correlation Matrices

Pooling correlation matrices

- REM
- Diagonal constraints of the heterogeneity matrix

```r
# Combine correlation matrices using a REM
#
rem <- tssem1(TAMu$data, TAMu$n,
                method = "REM",
                RE.type = "Diag")

# Summarize the results
summary(rem)
```

Stage 1: Pooling Correlation Matrices

Pooling correlation matrices

- REM
- Diagonal constraints of the heterogeneity matrix

```
## 95% confidence intervals: z statistic approximation (robust=FALSE)
## Coefficients:
##              Estimate Std.Error    lbound    ubound z value  Pr(>|z|)
## Intercept1 0.4828802 0.0217706 0.4402105 0.5255498 22.1803 < 2.2e-16 ***
## Intercept2 0.6068160 0.0174683 0.5725787 0.6410533 34.7381 < 2.2e-16 ***
## Intercept3 0.5153033 0.0254332 0.4654551 0.5651514 20.2611 < 2.2e-16 ***
## Intercept4 0.5276429 0.0209277 0.4866253 0.5686604 25.2127 < 2.2e-16 ***
## Intercept5 0.4089908 0.0220210 0.3658303 0.4521512 18.5727 < 2.2e-16 ***
## Intercept6 0.5187087 0.0259696 0.4678093 0.5696081 19.9737 < 2.2e-16 ***
## Tau2_1_1   0.0210148 0.0047131 0.0117772 0.0302524  4.4588 8.243e-06 ***
## Tau2_2_2   0.0134545 0.0030663 0.0074446 0.0194643  4.3878 1.145e-05 ***
## Tau2_3_3   0.0298527 0.0064754 0.0171612 0.0425443  4.6102 4.023e-06 ***
## Tau2_4_4   0.0195271 0.0044114 0.0108809 0.0281733  4.4265 9.578e-06 ***
## Tau2_5_5   0.0210140 0.0048452 0.0115176 0.0305103  4.3371 1.444e-05 ***
## Tau2_6_6   0.0312785 0.0066695 0.0182064 0.0443505  4.6898 2.735e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Stage 1: Pooling Correlation Matrices

Pooling correlation matrices

- REM
- Diagonal constraints of the heterogeneity matrix

```
## Q statistic on the homogeneity of effect sizes: 3622.948
## Degrees of freedom of the Q statistic: 294
## P value of the Q statistic: 0
##
## Heterogeneity indices (based on the estimated Tau2):
##                               Estimate
## Intercept1: I2 (Q statistic)    0.9178
## Intercept2: I2 (Q statistic)    0.9146
## Intercept3: I2 (Q statistic)    0.9460
## Intercept4: I2 (Q statistic)    0.9217
## Intercept5: I2 (Q statistic)    0.9015
## Intercept6: I2 (Q statistic)    0.9493
```

Stage 1: Pooling Correlation Matrices

Pooling correlation matrices

```
# Extract the pooled correlation matrix
corr.rem <- vec2symMat(coef(rem, select="fixed"), diag=FALSE)
colnames(corr.rem) <- c("PU", "PEU", "ATT", "BI")
rownames(corr.rem) <- c("PU", "PEU", "ATT", "BI")
corr.rem
```

```
##            PU       PEU       ATT        BI
## PU  1.0000000 0.4828802 0.6068160 0.5153033
## PEU 0.4828802 1.0000000 0.5276429 0.4089908
## ATT 0.6068160 0.5276429 1.0000000 0.5187087
## BI  0.5153033 0.4089908 0.5187087 1.0000000
```

Model Estimation

Model estimation

- Lavaan syntax possible
- Translate into the RAM framework

```
# Model specification
Model1 <- " # Structural parameters
            BI ~ ATT + PU
            ATT ~ PEU + PU
            PU ~ PEU

            # Variance of independent variables
            PEU ~~ 1*PEU
"
```

```
# Convert the model into the RAM language
RAM <- lavaan2RAM(Model1,
                  obs.variables = c("PU", "PEU", "ATT", "BI"))

```
```
```

Model Estimation

Model Estimation

```r
# Model estimation
# Confidence intervals are likelihood-ratio based (LBCIs)
TS.Model1 <- tssem2(rem, RAM = RAM,
            intervals.type="LB",
            diag.constraints = TRUE,
            model.name = "Model 1 with the direct effect")
```

```r
# Summarize the model parameters
summary(TS.Model1)
```

```
## 95% confidence intervals: Likelihood-based statistic
## Coefficients:
##              Estimate Std.Error  lbound  ubound z value Pr(>|z|)
## ATTONPEU      0.32668        NA 0.26635 0.38442      NA       NA
## ATTONPU       0.43668        NA 0.38557 0.48754      NA       NA
## BIONATT       0.35455        NA 0.26355 0.44470      NA       NA
## BIONPU        0.32253        NA 0.23013 0.41347      NA       NA
## PUONPEU       0.49973        NA 0.45797 0.54132      NA       NA
## ATTWITHATT    0.56001        NA 0.51662 0.60096      NA       NA
## BIWITHBI      0.63306        NA 0.58739 0.67590      NA       NA
## PUWITHPU      0.75027        NA 0.70697 0.79026      NA       NA
```

Model Estimation

Model Estimation

```r
# Summarize the model parameters
summary(TS.Model1)
```

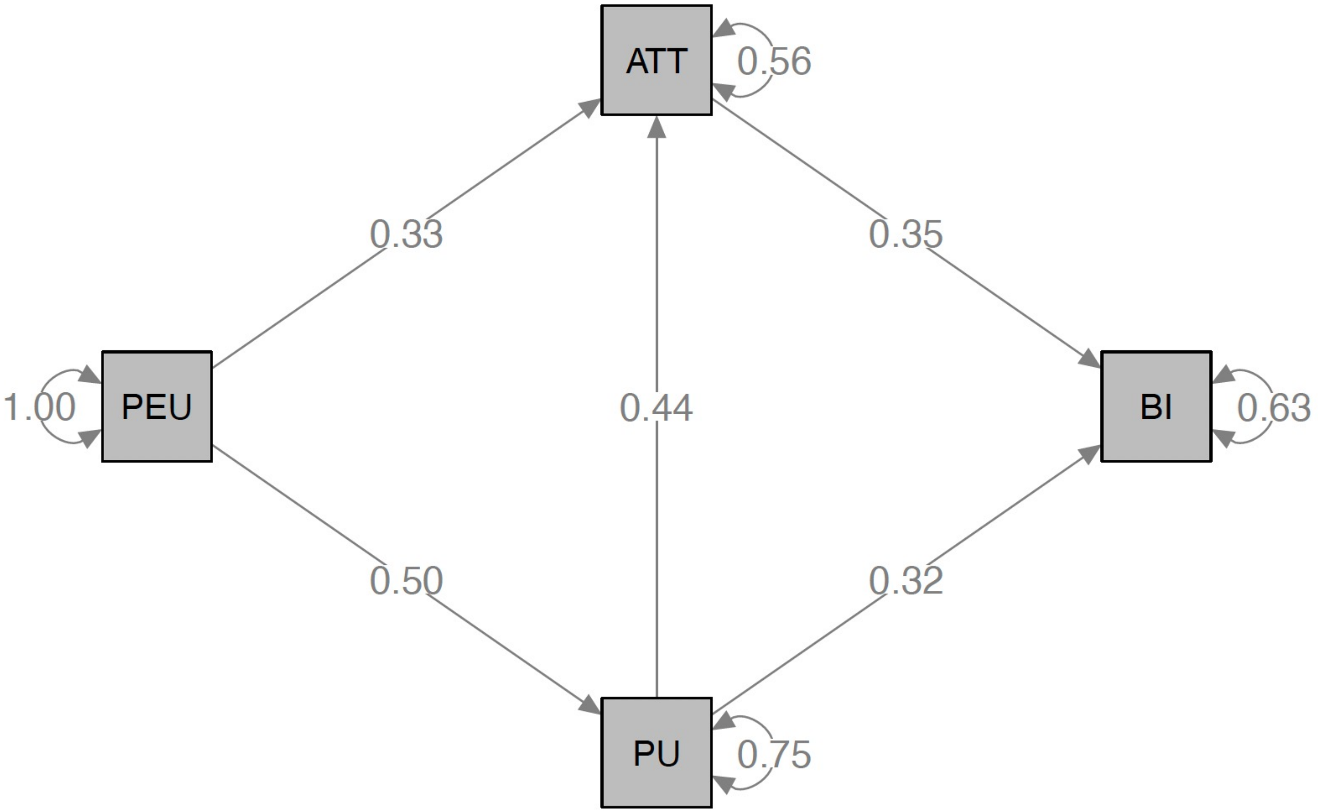
```
## Goodness-of-fit indices:
##                                                   Value
## Sample size                                  14918.0000
## Chi-square of target model                      10.0900
## DF of target model                               1.0000
## p value of target model                          0.0015
## Number of constraints imposed on "Smatrix"       3.0000
## DF manually adjusted                             0.0000
## Chi-square of independence model              3002.8440
## DF of independence model                         6.0000
## RMSEA                                            0.0247
## RMSEA lower 95% CI                               0.0125
## RMSEA upper 95% CI                               0.0395
## SRMR                                             0.0285
## TLI                                              0.9818
## CFI                                              0.9970
## AIC                                              8.0900
## BIC                                              0.4797
```

Model Estimation

Model Estimation

- Path diagram

```
# Visualize the model and add its parameters
TS.Model1.plot <- meta2semPlot(TS.Model1)
semPaths(TS.Model1.plot, whatLabels="est",
         rotation=2,
         edge.label.cex = 1.25,
         sizeMan = 8,
         color = "grey",
         layout = "tree2")
```

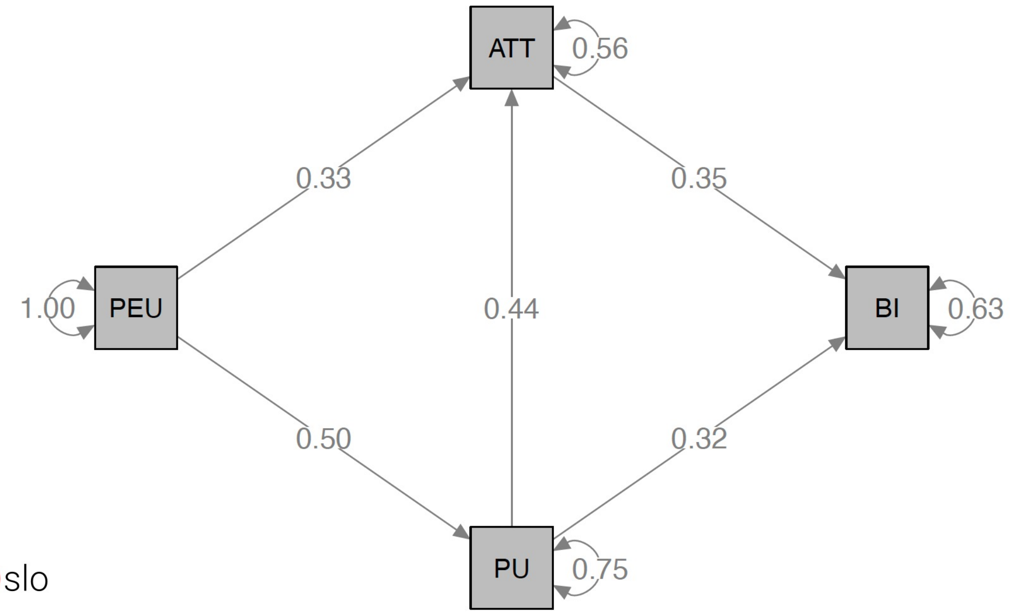


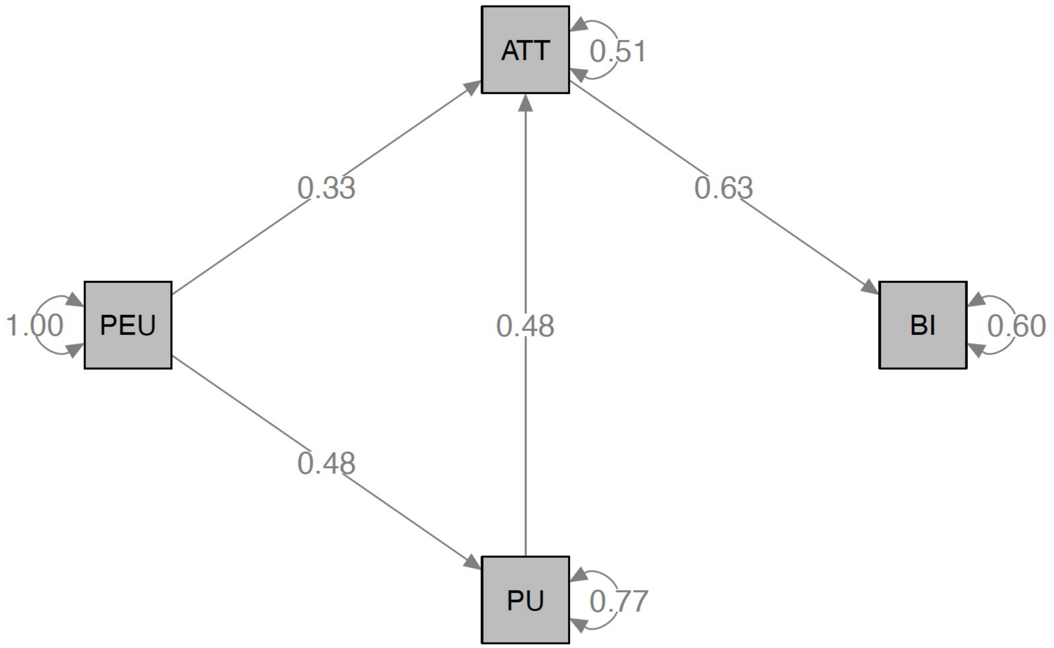
Model Comparison

Model Comparison

```
# Model comparison
anova(TS.Model1, TS.Model2)
```

Likelihood-ratio test: $\chi^2(1) = 42.1$, $p < .001$





UseR slo

Errors and Warnings

- Check whether the database was organized properly.
- Check Lavaan syntax.
- Rerun the model.

MASEM

Key potential

- Test and compare models representing substantive theory
- Examine heterogeneity in model parameters

Key challenges

- Multilevel structure of the primary and secondary data
- Heterogeneity

The End.

by Jf Brou on Unsplash

Twitter: diegc_
Email: diegogc@uio.no
Webpage: www.diegocampos.co

References

Cheung, M. W.-L. (2013). Multivariate meta-analysis as structural equation models. Structural Equation Modeling, 20(3), 429-454. https://doi.org/10.1080/10705511.2013.797827

Cheung, M. W.-L. (2015). Meta-Analysis: A Structural Equation Modeling Approach. John Wiley & Sons Ltd.

Cheung, M. W.-L., & Cheung, S. F. (2016). Random-effects models for meta-analytic structural equation modeling: review, issues, and illustrations. Research Synthesis Methods, 7(2), 140-155. https://doi.org/10.1002/jrsm.1166

Cheung, M. W.-L. (2018). Issues in solving the problem of effect size heterogeneity in meta-analytic structural equation modeling: A commentary and simulation study on Yu, Downes, Carter, and O'Boyle (2016). Journal of Applied Psychology, 103(7), 787-803. http://dx.doi.org/10.1037/apl0000284

Jak, S., & Cheung, M. W. (2018, November 23). Meta-Analytic Structural Equation Modeling with Moderating Effects on SEM Parameters. https://doi.org/10.31234/osf.io/ce85j

Scherer, R., & Teo, T. (2019). Unpacking teachers' intentions to integrate technology: A meta-analysis. Educational Research Review, 27, 90-109. https://doi.org/10.1016/j.edurev.2019.03.001