Meta-analytic SEM in Development of TAM Models

Adam Sagan Mariusz Grabowski

Cracow University of Economics

Outline

TAM Models

1. Technology Acceptance Model (TAM) and its derivatives, e.g. UTAUT (Unified Theory of Acceptance and Use of Technology) belong to the most frequently used theoretical frameworks to interpret behavior of users with regard to IT/IS artifacts and their acceptance (Davis, 1989; Davis, Bagozzi and Warshaw 1989)
2. Theoretical foundations of TAM: Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) (Ajzen, 1985)
3. Many of research is based on structural equation (SEM) and partial least squares (PLS-PM) approaches (Sagan and Grabowski 2015)

Meta-analysis of TAM models

1. Selection of papers, published in the three leading scientific journals of Information Systems (IS) community, namely: *MIS Quarterly* (MISQ - IF 2015 = 5.384), *Information Systems Research* (ISR - IF 2015 = 3.047) and *Information Systems Journal* (ISJ - 2015 IF = 2.522)
2. The collection of 29 papers published over the 24 years (from 1991-2014). American (MISQ and ISR) periodicals prevail in the structure of the publications, given that 23 articles constitute almost 80% of the total collection
3. Finally, 55 studies were selected for the meta-analytic SEM

Meta-analytic structural equation modeling (MASEM)

1. Meta-analysis (MA) is the statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings (Glas 1976; 3). It allows to generalize the findings across studies, identify potential moderators in the model structure and obtain the appropriate estimates given a larger sample sizes
2. Structural equation models (SEM) is a powerful statistical method for estimation multivariate regression models with latent variables that combines regression analysis with (confirmatory) factor analysis
3. MASEM is an integration of MA and SEM that gives sufficient improvements in the estimation of structural equation models: 1/ structural equation modelling requires large sample sizes while combining the information from many samples and studies may increase the statistical power, 2/ in many individual studies only partial solution to given research questions may exist

Approaches to MASEM modeling

1. Generally, two-stage approach is used: 1/ testing the homogeneity of correlation matrices and estimation of pooled correlation matrix 2/ estimation of SEM models based on pooled correlation matrix
2. Pooled correlation matrix estimation: 1/ univariate approach – calculation of weighted correlations or weighed Fisher – z scores, 2/ multivariate approach – multigroup generalized least squares (GLS) or two-stage structural equation modelling (TSSEM), based on all correlation coefficients
3. Types of MASEM models: 1/ fixed – effect SEM (correlations, covariances, path coefficients etc. are assumed to be homogeneous across studies) 2/ random-effect SEM (effect sizes may vary due to differences in samples and methods used in different studies) and 3/ mixed-effect SEM (models with covariates and both fixed and random effects)

Meta-analytic SEM of TAM models

1. Data consisted of the correlations between constructs in original TAM model
2. The correlations were gathered from 55 studies identified in 29 publications in contemporary scholarly journals from the IS field

	Name	Year	Source	Sample size	UE	UB	EB
1	Agarwal	2000	(J)	288	0.55	0.65	0.57
2	Agarwal	1999	(J)	230	0.74	0.45	0.36
3	Aladwani	2002	(J)	387	0.37	0.44	0.39
4	An	2005	(D)	200	0.71	0.68	0.48
5	Busch	1995	(D)	249	0.21	0.57	0.23
6	Davis	1989	(J)	80	0.56	0.85	0.59
7	Featherman	2002	(D)	215	0.59	0.71	0.54
8	Featherman	2003	(C)	167	0.63	0.72	0.58
9	Gefen	2003	(J)	161	0.64	0.48	0.38
10	Gefen	2003a	(J)	139	0.75	0.18	0.1
11	Gefen	2003a	(J)	178	0.72	0.38	0.35

3. The estimations were calculated using **metaSEM** and **OpenMx** libraries of R package and **Mplus** program for structural equation modeling

Pooled correlation matrix

1. For meta-analytic SEM only limited version of TAM model was tested that involves the relationships between perceived ease of use (E), perceived usefulness (U) and behavioral intention of use (B)

```
    N   UE   UB   EB
1 288 0.55 0.65 0.57
2 230 0.74 0.45 0.36
3 387 0.37 0.44 0.39
4 200 0.71 0.68 0.48
5 249 0.21 0.57 0.23
6  80 0.56 0.85 0.59
```

```
> cormatrices
[[1]]
     U    E    B
U 1.00 0.55 0.65
E 0.55 1.00 0.57
B 0.65 0.57 1.00

[[2]]
     U    E    B
U 1.00 0.74 0.45
E 0.74 1.00 0.36
B 0.45 0.36 1.00

[[3]]
     U    E    B
U 1.00 0.37 0.44
E 0.37 1.00 0.39
B 0.44 0.39 1.00
```

2. Pooled correlation matrix was estimated using two-stage approach

```
Coefficients:
        Estimate  Std.Error z value  Pr(>|z|)
S[1,2] 0.5467940 0.0069134  79.092 < 2.2e-16 ***
S[1,3] 0.4542316 0.0077968  58.259 < 2.2e-16 ***
S[2,3] 0.6010102 0.0062973  95.439 < 2.2e-16 ***
```

Pooled correlation matrix – random effect model

1. Average (pooled) correlations (**Intercept**) and between – study variances of correlation coefficients as random effects (**Tau**).

```
Coefficients:
             Estimate Std.Error    lbound    ubound z value  Pr(>|z|)
Intercept1 0.5482583 0.0210541 0.5069930 0.5895236 26.0404 < 2.2e-16 ***
Intercept2 0.4677038 0.0206228 0.4272838 0.5081238 22.6790 < 2.2e-16 ***
Intercept3 0.6003339 0.0191124 0.5628743 0.6377936 31.4107 < 2.2e-16 ***
Tau2_1_1   0.0196798 0.0044335 0.0109903 0.0283693  4.4389 9.043e-06 ***
Tau2_2_2   0.0181367 0.0041191 0.0100633 0.0262100  4.4030 1.068e-05 ***
Tau2_3_3   0.0162390 0.0036416 0.0091015 0.0233764  4.4593 8.224e-06 ***
```

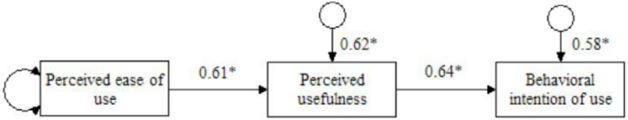
2. Q tests of effect sizes homogeneity across studies suggests strong heterogeneity

```
Q statistic on the homogeneity of effect sizes: 1561.897
Degrees of freedom of the Q statistic: 153
P value of the Q statistic: 0

Heterogeneity indices (based on the estimated Tau2):
                              Estimate
Intercept1: I2 (Q statistic)    0.9100
Intercept2: I2 (Q statistic)    0.8731
Intercept3: I2 (Q statistic)    0.9113
```

MASEM model of technology acceptance

1. TAM structural equation model based on pooled correlation matrix was estimated using **OpenMx** and **tssem2** libraries of R package and weighted least squares (WLS) estimation



2. The aggregate sample size is 10766. Chi-square of target model is 67.01 with 1 df and p-value = 0.000. The RMSEA is marginally acceptable 0.078 (CI: 0.063 - 0.095) and comparative fit indices TLI and CFI are respectively 0.83 and 0.94

Empirical research on primary data

1. The parameters of the MASEM model are used as an a priori information for Bayesian SEM model on primary data. The use of a priori information is a distinctive advantage of Bayesian models (Rossi, Allenby and McCulloch, 2005)
2. The data were based on quota sample of 150 students of Cracow University of Economics using Moodle platform majoring in Applied Informatics
3. The constructs of TAM model were measured on 7-point Likert scales

Use of MASEM results for estimation of TAM model

Paths and residuals	Estimate	P-level
MASEM model		
UE	0.61	0.00
UB	0.64	0.00
Residual U	0.62	0.00
Residual B	0.58	0.00
Model goodness of fit	Chi-Square Value = 67.01, p=0.00, RMSEA = 0.078, CFI = 0.94	
Bayesian SEM model		
UE	0.83	0.00
UB	0.27	0.00
Residual U	0.31	0.00
Residual B	0.32	0.00
Model goodness of fit	95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values : 192.417 - 276.225, Posterior Predictive P-Value = 0.00	

1. The results show significant discrepancies between MASEM and BSEM models. It may suggest that parameters obtained in primary data research are biased due to a small and non-representative sample
2. The direction of bias is clearly defined. The U-E regression is upwardly biased and U-B regression is downwardly biased as compared with the world's meta-analytic data

Conclusions

1. The integration of meta-analysis and SEM models provides a powerful tool for a model generation and parameter check
2. The results of metaanalytic SEM is useful for a priori information for bayesian SEM models
3. In the result of contrasting the local findings with the findings of meta-analytic SEM models, the researcher gains an important knowledge concerning stability of model parameters, representativeness of the results and the direction of potential bias