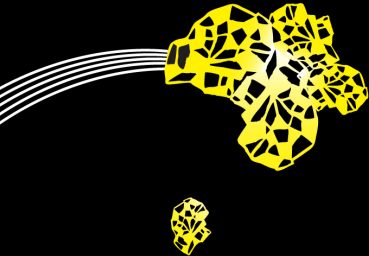


Confirmatory Composite Analysis

What is it & how is it applied?



Florian Schuberth¹

¹University of Twente

October 8, 2020



Overview

- 1 History of Confirmatory Composite Analysis
- 2 Confirmatory Composite Analysis
 - Model Specification
 - Model Identification
 - Model Estimation
 - Model Assessment
- 3 Demonstration

Who am I?

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- 2007 - 2010: Bachelor in Business Administration & Economics;
University of Würzburg, GER
- 2010 - 2012: Master in Economics;
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- 2012 - 2017: PhD in Econometrics (M. Kukuk & J. Henseler);
University of Würzburg, GER
- 2017 - present: Assistant professor;
Product-Market Relations at the University of Twente, NL

1 History of Confirmatory Composite Analysis

2 Confirmatory Composite Analysis

- Model Specification
- Model Identification
- Model Estimation
- Model Assessment

3 Demonstration

History of CCA

In 2014, CCA was first mentioned as an approach to assess the overall fit of a composite model¹

well does PLS perform if the composite factor model is indeed correct?” Preliminary findings give rise to optimism for both these questions: PLS serves well for predictive purposes (Becker, Rai, & Rigdon, 2013), and when the composite factor model is true, PLS clearly outperforms covariance-based SEM and regression on sum scores (Rai et al., 2013). In conclusion, PLS is not a panacea, but certainly an important technique deserving a prominent place in any empirical researcher’s statistical toolbox.

Authors’ Note

The formal development of the composite factor model is attributable to the second author, and in collaboration with the first author developed into the concept of confirmatory composite analysis. The authors thank Dr. Rainer Schlittgen, Professor of Statistics and Econometrics, University of Hamburg, Germany, for helpful comments on earlier versions of the article.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

¹Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, 17(2), 182–209.

History of CCA

In 2018, CCA was fully elaborated² and in 2020, it was introduced to business research³



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Confirmatory Composite Analysis

Rolfen Schuberth^{1,2,3}, Jörg Henseler^{1,4} and Theo K. Dijkstra⁵

¹University of Leoben, Leoben, Austria; ²University of Leoben, Leoben, Austria; ³University of Leoben, Leoben, Austria; ⁴University of Leoben, Leoben, Austria; ⁵University of Leoben, Leoben, Austria

This article introduces confirmatory composite analysis (CCA) as a structural equation modeling technique that aims at testing composite models. It facilitates the quantification and assessment of design concepts, so-called artifacts. CCA entails the same steps as confirmatory factor analysis: model specification, model identification, model estimation, and model assessment. Composite models are specified such that they consist of a set of identified components, all of which emerge as linear combinations of observable variables. Researchers must ensure theoretical identification of the specified model. For the estimation of the model, several estimators are available; in particular, maximum likelihood estimation of structural equation models provides consistent estimates. Model assessment mainly relies on the Fisher-Spearman bootstrap to assess the discrepancy between the empirical and the estimated model-implied covariance matrix. A Monte Carlo simulation assesses the efficacy of CCA, and demonstrates that CCA is able to detect various forms of model misspecification.

KEYWORDS: confirmatory composite analysis, confirmatory factor analysis, confirmatory structural equation modeling, bootstrapping, structural equation modeling, bootstrapping

1. INTRODUCTION

Structural equation modeling with latent variables (SEM) comprises confirmatory factor analysis (CFA) and path analysis, thus facilitating methodological developments from different disciplines such as psychology, sociology, and economics, while covering a broad variety of statistical multivariate statistical procedures (Jöreskog, 1993; Bollen, 1989). It is a special case of representing theoretical concepts by means of highly observable indicators to connect them to the structural model as well as to account for measurement error. Since SEM allows for statistical testing of the estimated parameters and even entire models, it is an understanding tool for confirmatory purposes such as for assessing construct validity (Jöreskog and Sörbom, 1993). In fact, for confirming measurement validity (Jöreskog and Sörbom, 1993), SEM is the most rigorous method for testing theoretical hypotheses and a number of alternative estimators were also introduced to maximize robustness of the model fit (Jöreskog and Sörbom, 1993). Over time, the latent variable model has been considerably improved to account for more complex distributions (e.g., Jöreskog and Sörbom, 1993) or for the two-stage least squares (2SLS) estimator (Jöreskog, 1993). However, SEM is still to deal with categorical indicators (Jöreskog and Sörbom, 1993) and can be used to model non-linear relationships between the constructs (Jöreskog and Sörbom, 1993).

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Using confirmatory composite analysis to assess emergent variables in business research^{a,b}

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Model identification

Model estimation

Model specification

Model testing

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ABSTRACT

Confirmatory composite analysis (CCA) was reviewed by Jörg Schuberth and Theo K. Dijkstra in 2018 and was extended by Schuberth et al. (2018) to a comparison of procedures for specifying and assessing composite models. Composite models consist of one or more theoretical constructs and all while emerge as linear combinations of observable variables. Researchers must ensure theoretical identification of the specified model. For the estimation of the model, several estimators are available; in particular, maximum likelihood estimation of structural equation models provides consistent estimates. Model assessment mainly relies on the Fisher-Spearman bootstrap to assess the discrepancy between the empirical and the estimated model-implied covariance matrix. A Monte Carlo simulation assesses the efficacy of CCA, and demonstrates that CCA is able to detect various forms of model misspecification.

1. Introduction

Modeling and testing theories that contain distinct constructs is a core part of a large number of studies in business research. The validity of statistical tests provided for this purpose, constant structural equation models (CSEM), play a crucial role in the process. Methodological papers on CCA were first published in 1970 (Jöreskog and Sörbom, 1970) and were revised in 1993 (Jöreskog and Sörbom, 1993). In 2018, Schuberth et al. (2018) reviewed the literature on CCA and presented a comparison of procedures for specifying and assessing composite models. Composite models consist of one or more theoretical constructs and all while emerge as linear combinations of observable variables. Researchers must ensure theoretical identification of the specified model. For the estimation of the model, several estimators are available; in particular, maximum likelihood estimation of structural equation models provides consistent estimates. Model assessment mainly relies on the Fisher-Spearman bootstrap to assess the discrepancy between the empirical and the estimated model-implied covariance matrix. A Monte Carlo simulation assesses the efficacy of CCA, and demonstrates that CCA is able to detect various forms of model misspecification.

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^a This paper was submitted for publication as a special issue in confirmatory composite analysis (https://doi.org/10.3389/fpsyg.2018.2541).

^{b</}

In memory and special thanks



Theo K. Dijkstra
*17.06.1953 - †14.09.2020

1 History of Confirmatory Composite Analysis

2 Confirmatory Composite Analysis

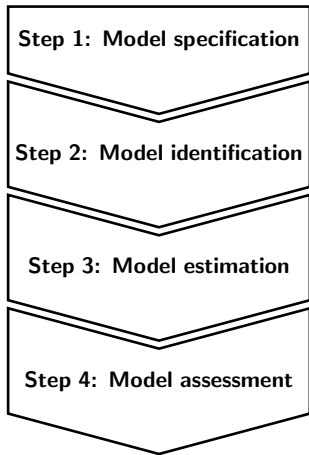
- Model Specification
- Model Identification
- Model Estimation
- Model Assessment

3 Demonstration

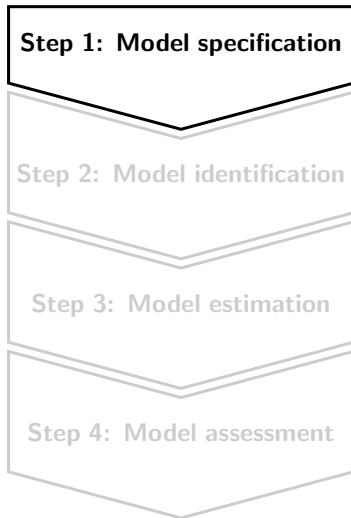
Confirmatory composite analysis

Like all approaches to SEM, CCA consists of four steps

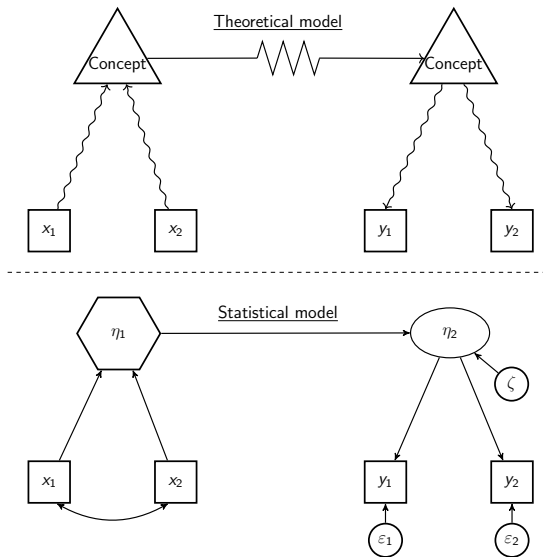
Confirmatory composite analysis



Confirmatory composite analysis

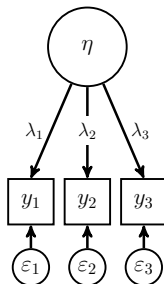


Model specification



Two types of concepts

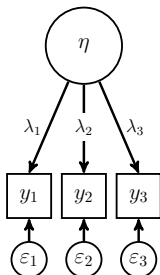
Type of concept:	Theoretical concept
Type of construct:	Latent variable
Dominant statistical model:	Common factor model



Statistical approach:	Confirmatory factor analysis
Examples:	Attitudes, traits

Two types of concepts

Type of concept:	Theoretical concept	Forged concept
Type of construct:	Latent variable	Emergent variable
Dominant statistical model:	Common factor model	Composite model

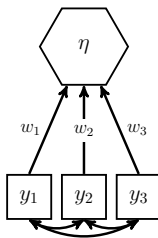


Statistical approach:

Confirmatory factor analysis

Examples:

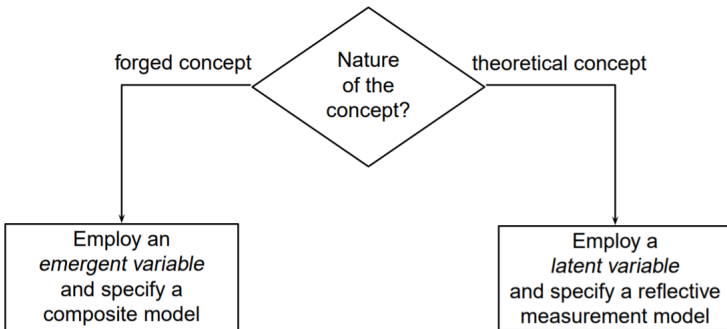
Attitudes, traits



Confirmatory composite analysis

Capabilities, indices, values

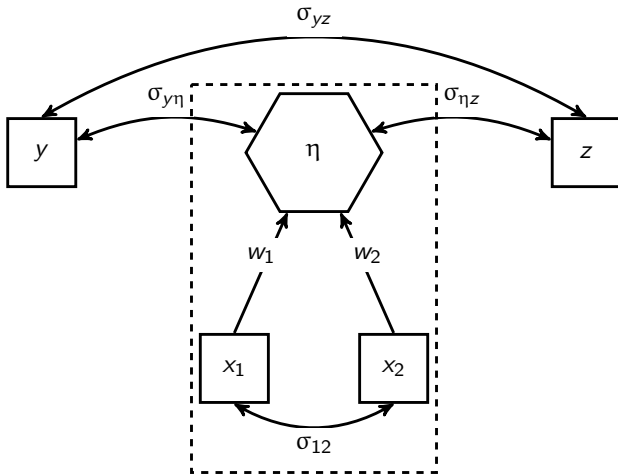
Decision



Decision about the outer model⁴

⁴Henseler, J. (in press). *Composite-based structural equation modeling: Analyzing latent and emergent variables*. New York, The Guilford Press.

Example specification



Minimal composite model

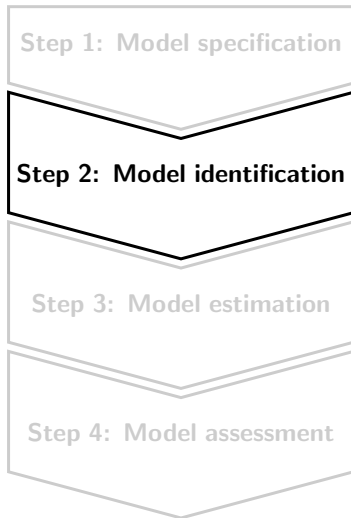
Model-implied variance-covariance matrix

The model-implied variance-covariance matrix $\Sigma(\theta)$ of the minimal composite model:

$$\Sigma(\theta) = \begin{pmatrix} \underline{y} & \underline{x_1} & \underline{x_2} & \underline{z} \\ \sigma_{yy} & & & \\ \lambda_1 \sigma_{y\eta} & \sigma_{11} & & \\ \lambda_2 \sigma_{y\eta} & \sigma_{12} & \sigma_{22} & \\ \sigma_{yz} & \lambda_1 \sigma_{\eta z} & \lambda_2 \sigma_{\eta z} & \sigma_{zz} \end{pmatrix},$$

where $\lambda_1 = \text{cov}(x_1, \eta)$ and $\lambda_2 = \text{cov}(x_2, \eta)$.

Confirmatory composite analysis



Model identification

Parameters in $\Sigma(\theta)$ can be uniquely retrieved from the population variance-covariance matrix Σ .

For the minimal composite model:

$$\begin{pmatrix} \underline{y} & \underline{x_1} & \underline{x_2} & \underline{z} \\ \sigma_{yy} & & & \\ \lambda_1 \sigma_{y\eta} & \sigma_{11} & & \\ \lambda_2 \sigma_{y\eta} & \sigma_{12} & \sigma_{22} & \\ \sigma_{yz} & \lambda_1 \sigma_{\eta z} & \lambda_2 \sigma_{\eta z} & \sigma_{zz} \end{pmatrix} = \begin{pmatrix} \underline{y} & \underline{x_1} & \underline{x_2} & \underline{z} \\ \sigma_{yy} & & & \\ \sigma_{y1} & \sigma_{11} & & \\ \sigma_{y2} & \sigma_{12} & \sigma_{22} & \\ \sigma_{yz} & \sigma_{1z} & \sigma_{2z} & \sigma_{zz} \end{pmatrix}$$

- | | | |
|--|---|---|
| (1) $\sigma_{yy} = \sigma_{yy}$ | (2) $\lambda_1 \sigma_{y\eta} = \sigma_{y1}$ | (3) $\sigma_{11} = \sigma_{11}$ |
| (4) $\lambda_2 \sigma_{y\eta} = \sigma_{y2}$ | (5) $\sigma_{12} = \sigma_{12}$ | (6) $\sigma_{22} = \sigma_{22}$ |
| (7) $\sigma_{yz} = \sigma_{yz}$ | (8) $\lambda_1 \sigma_{\eta z} = \sigma_{1z}$ | (9) $\lambda_2 \sigma_{\eta z} = \sigma_{2z}$ |
| (10) $\sigma_{zz} = \sigma_{zz}$ | | |

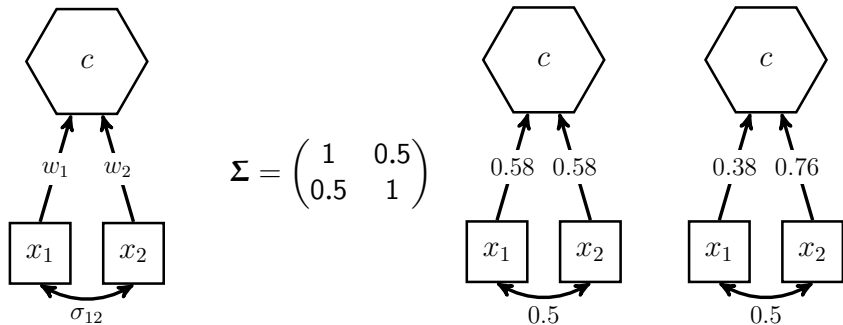
Identification rules

Identification of composite models is straightforward:⁵

- ▶ Fix scale of all emergent variables, e.g., $\mathbf{w}_j' \Sigma_{jj} \mathbf{w}_j = 1$
 - ▶ Each emergent variable must be connected to at least one emergent variable or variable not forming the emergent variable
 - (▶ Structural model needs to be identified)
- ⇒ All model parameters can be uniquely retrieved from the population indicator covariance matrix

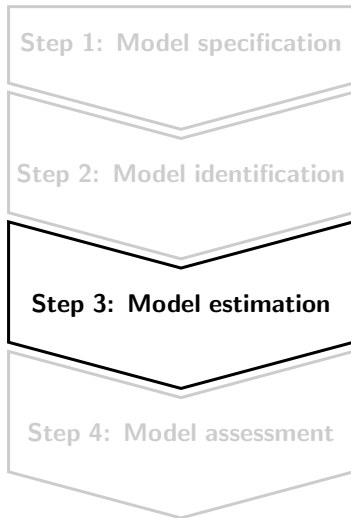
⁵Ignoring trivial regularity assumptions such as weight vectors consisting of zeros only; and similarly, we ignore cases where intra-block covariance matrices are singular.

Not identified composite model



Infinite number of weight sets satisfying the scaling condition, i.e., variance of emergent variable equals 1: $\mathbf{w}'\Sigma\mathbf{w} = 1$.

Confirmatory composite analysis



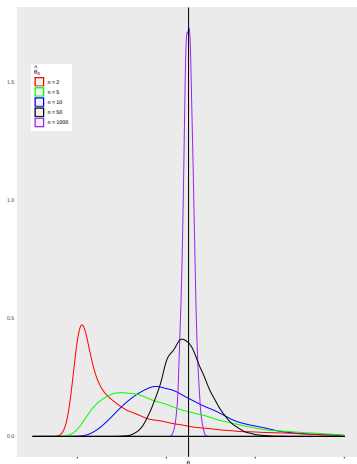
Model estimation

Typically the population parameters θ are unknown as we only have a sample at hand

⇒ Model parameters need to be estimated based on a sample (which is representative of the considered population)

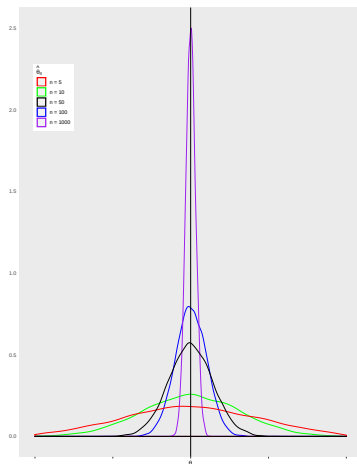
Which estimator to choose?

Consistent estimator



$$\text{plim } \hat{\theta} = \theta$$

Unbiased estimator



$$E(\hat{\theta}) = \theta$$

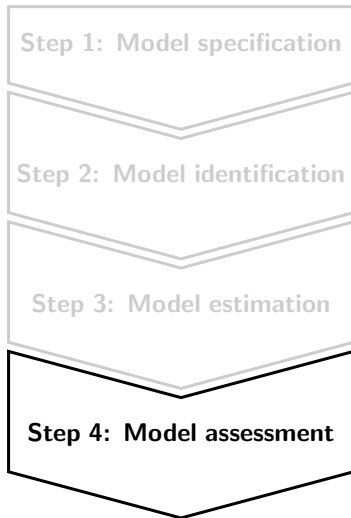
Potential Candidates

To estimate the parameters, several methods can be used:

- ▶ Approaches to generalized canonical correlation analysis (GCCA) such as MAXVAR (Kettenring, 1971)
- ▶ Regularized general canonical correlation analysis (RGCCA, Tenenhaus & Tenenhaus, 2011)
- ▶ Iterative partial least squares algorithm (PLS, Wold, 1975)
- ▶ Generalized structured component analysis (GSCA, Hwang & Takane, 2004)
- ▶ Maximum-likelihood estimator

Predetermined weights such as unit weights or expert weights are also conceivable.

Confirmatory composite analysis



Model assessment

Model assessment consists of two steps:

- ▶ Overall model fit assessment
- ▶ Assessment of the emergent variables

Overall model fit assessment

Overall model fit assessment is crucial to investigate whether the model is an acceptable description of reality.

The overall model fit can be assessed in two non-exclusive ways:

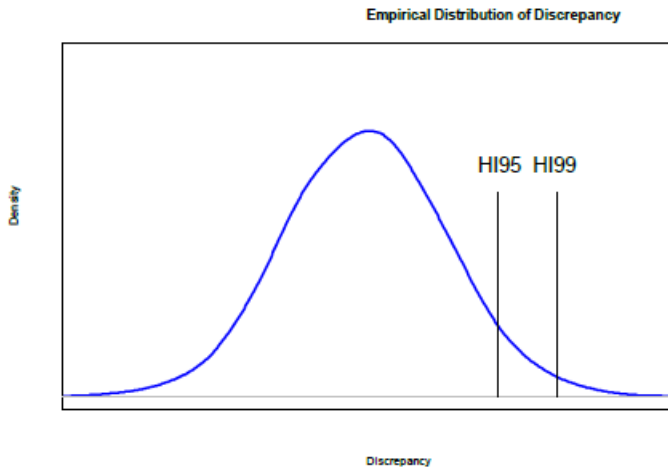
- ▶ Test for exact model fit
- ▶ Fit indices (heuristic rules)

Test for exact model fit

To test the exact model fit ($H_0 : \Sigma = \Sigma(\theta)$), a bootstrap-based test was proposed for CCA (Beran & Srivastava, 1985; Schuberth et al., 2018) in combination with various discrepancy measures such as

- ▶ Standardized root mean squared residual (SRMR)
- ▶ Geodesic distance (d_G)
- ▶ Squared Euclidean distance (d_L)

Bootstrap-based test for exact model fit



Fit indices

Tests for exact model fit are often regarded as too stringent.

The hypothesis of exact fit is often regarded as not plausible: “All models are wrong” (Box, 1976)

Approximate fit indices such as

- ▶ Standardized root mean squared residual (SRMR, Bentler, 1995; Schuberth et al., 2018), and
- ▶ Goodness of fit index (GFI, Cho et al., accepted; Jöreskog & Sörbom, 1989)

quantify the degree of misfit.

⇒ The larger their value, the larger the misfit.

Criticism on fit indices

Fit indices have been criticized:

- ▶ Fit indices are descriptive and non-inferential
- ▶ Derived thresholds are subjective and arbitrary

Assessment of emergent variables

Do the estimates align with your theory?

Compare

- ▶ estimated parameters,
- ▶ sign of the estimates, and
- ▶ significance of the estimate

with your expectations/theory

Assess potential multicollinearity issues, e.g., consider variance inflation factor.

Confusion

In 2020, CCA was dubbed as the method of confirming measurement quality (MCMQ) in PLS-SEM (Hair et al., 2020)

Problem

CCA and MCMQ are not the same!



Difference between CCA and MCMQ

Differences between CCA and MCMQ⁶

	Confirmatory composite Analysis	Method of confirming measurement quality
Purpose:	Assessing composite models.	Confirming the quality of reflective and formative measurement models.
Steps:	Model specification, model identification, model estimation, model assessment.	Seven steps to assess reflective measurement models and five steps to assess formative measurement models.
Relation to PLS:	Not tied to PLS, but it can serve as an estimator.	MCMQ is the evaluation step of PLS-SEM.
Role of Fit:	Assessment of model fit is an essential step of CCA.	MCMQ does not require the assessment of model fit.
Efficacy:	Evidence of its efficacy (mathematical and empirical).	Counterevidence of its efficacy.

⇒ Make sure to not confuse the CCA and MCMQ

⁶Schuberth, F. (2021). Confirmatory composite analysis using partial least squares: Setting the record straight. *Review of Managerial Science*, 15(1).

1 History of Confirmatory Composite Analysis

2 Confirmatory Composite Analysis

- Model Specification
- Model Identification
- Model Estimation
- Model Assessment

3 Demonstration

Demonstration

Considering Value of Destination Experience (VDE)⁷:

“Also, there is one more second-order construct for the perceived value of destination **formed** from a scale measuring functional, social, and emotional value” (Lee et al., 2018, p.492)

Hypothesis:

VDE emerges from Functional, Social and Emotional Values within its environment.

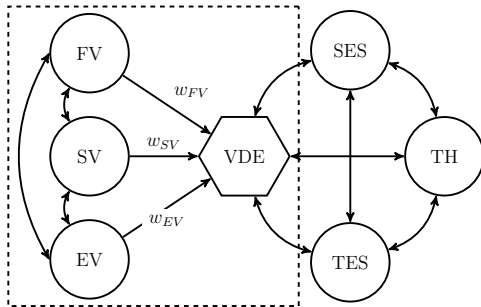
VDE's environment consists of:

- ▶ Service Experience Satisfaction (SES)
- ▶ Travel Experience Satisfaction (TES)
- ▶ Tourist Happiness (TH)

⁷Lee, H., Lee, J., Chung, N., & Koo, C. (2018). Tourists' happiness: Are there smart tourism technology effects? *Asia Pacific Journal of Tourism Research*, 23(5), 486–501.

Demonstration

Model specification:



Model identification:

- Scale of the emergent variable is fixed (ensured by PLS)
- Emergent variable is not isolated

⇒ Model is identified

Demonstration

To conduct the analysis, ADANCO can be used:
<https://www.composite-modeling.com/>



Similarly, the R package cSEM can be used:
<https://github.com/M-E-Rademaker/cSEM>



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Appendix

Steps in ADANCO

Construct characteristics

Name:

Reliability:

Type of constr...

Weighting sche...

Dominant indic...

Indicators

Leeeta2018.xlsx (2020-10-07 11:13)

- ✗ INFO
- ✗ ACC
- ✗ INT
- ✗ PER
- ✓ FV
- ✓ SV
- ✓ EV
- ✗ SES
- ✗ TES
- ✗ TH

Model VDE ✕

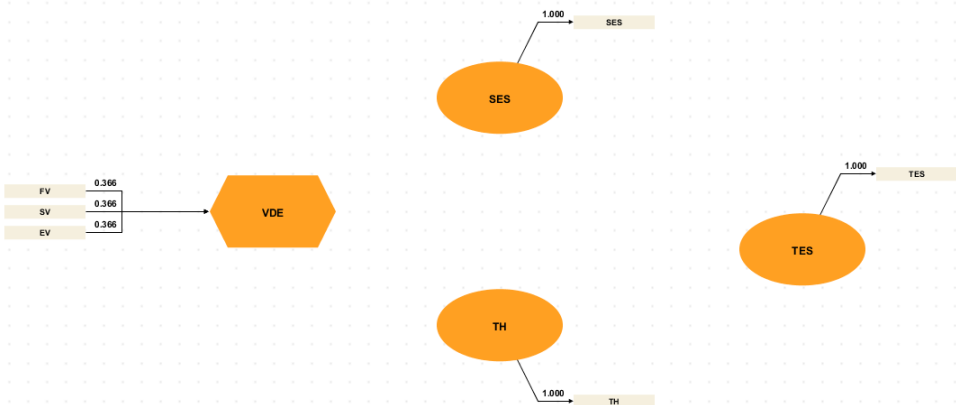
Model STE ✕

Model 1 ✕

Model 2 ✕

FV	0.366
SV	0.366
EV	0.366

VDE





Run



Calculation profile:

Default

Edit profiles

Models

- ☐ Model VDE
- ☐ Model STE
- ☐ Model 1
- ☒ Model 2

Algorithm Settings

Stop Criterion:

1.0E-6

Maximum number of iterations:

200

Inner weighting scheme:

Centroid

Missing Value Treatment

☒ Casewise deletion

☐ Mean imputation

☐ Median imputation

☐ Constant value

0

☐ Random imputation Seed:

0

Generate

☒ Use bootstrapping ☒ Assess model fit

Bootstrapping

Seed:

0

Generate

Bootstrap samples:

999

Cancel

Default Settings

Save Settings

Save and Run

376

213

506

1.1

S
0.644

