

# A structural-after-measurement (SAM) approach for latent moderation

Yves Rosseel

*Department of Data Analysis, Ghent University (Belgium)*

## **Topic:** Moderation Effects in Latent Variables

Several methods have been proposed to include quadratic or interaction terms involving latent variables in structural equation models. Some examples are the latent moderated structural equations approach (LMS; Klein & Moosbrugger, 2000), the nonlinear structural equation mixture approach (NSEMM; Kelava & Brandt, 2014), and several variants of the product indicator (PI) approach (Kenny & Judd, 1984; Marsh, Wen, & Hau, 2004). All these methods use a system-wide estimation approach and estimate the free parameters of the model simultaneously. This is in contrast to the 2-stage method of moments estimator (2SMM; Wall & Amemiya, 2003) where factor scores are computed in a first stage, and an errors-in-variable regression approach is used in the second stage. In this presentation, I will describe an alternative approach that is similar in spirit to 2SMM, but where we avoid the explicit calculation of factor scores. The approach builds on the (local) structural-aftermeasurement (SAM) approach that was recently proposed by Rosseel & Loh (in press). Just like 2SMM, we first estimate the parameters of the measurement part of the model in stage one. The measurement parameters, together with the sample statistics, are then used to construct an estimate of the variance-covariance matrix of the latent variables:  $\text{Var}(\eta)$ . This variance-covariance matrix is used in the second stage, where we estimate the (linear) relationships among the latent variables. It turns out that we can also derive explicit expressions for  $\text{Var}(\eta \otimes \eta)$  and  $\text{Cov}(\eta, \eta \otimes \eta)$  where  $\otimes$  denotes the Kronecker product (Burghgraeve, 2021). This allows for easy inclusion of quadratic and interaction terms in the structural part of the model. Preliminary simulation results indicate that the approach works well, even in the presence of distributional and structural misspecifications.

## **References**

- Klein, A.G. & Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. *Psychometrika*, 65, 457–474.
- Kelava, A. & Brandt, H. (2014). A general nonlinear multilevel structural equation mixture model. *Frontiers in Psychology*, 5, 748.
- Kenny, D. & Judd, C.M. (1984). Estimating the nonlinear and interactive effects of latent variables. *Psychological Bulletin* 96, 201–210.
- Marsh, H.W., Wen, Z., & Hau, K.-T. (2004). Structural equation models of latent interactions: evaluation of alternative estimation strategies and indicator construction. *Psychological Methods* 9, 275–300.
- Wall, M.M. & Amemiya, Y. (2000). Estimation for polynomial structural equation models. *Journal of the Statistical American Association*, 95, 929–940.
- Rosseel, Y. & Loh, W.W. (in press). A structural after measurement (SAM) approach to structural equation modeling. *Psychological Methods*. (preprint: <https://osf.io/pekbm/>)
- Burghgraeve, E. (2021). Alternative estimation procedures for structural equation models. Unpublished PhD thesis.