

Full latent growth and its use in PLS-SEM: Testing moderating relationships

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Abstract

A full latent growth analysis, in the context of structural equation modeling via partial least squares (PLS-SEM), can be viewed as a comprehensive analysis of moderating effects where the moderating variable is “latent”, not “disrupting” the model in any way. In this paper we illustrate such an analysis employing WarpPLS, a leading PLS-SEM software tool.

Keywords: Full Latent Growth; Nonlinear Relationship; Moderating Relationship; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

Structural equation modeling (SEM) allows researchers to build causal models with latent variables. These latent variables are measured indirectly through other variables, called indicators. Partial least squares (PLS) methods have been increasingly used for SEM. Classic PLS-SEM algorithms estimate latent variables as composites, without explicitly accounting for measurement error.

Modern PLS-SEM algorithms, on the other hand, estimate latent variables as factors, leading to more precise estimates (Kock, 2019a; 2019b). WarpPLS is a leading PLS-SEM software tool that implements these modern factor-based algorithms. We use WarpPLS version 7.0 to illustrate our analyses in this paper. Our focus in this paper is on full latent growth and its use in PLS-SEM to test moderating relationships.

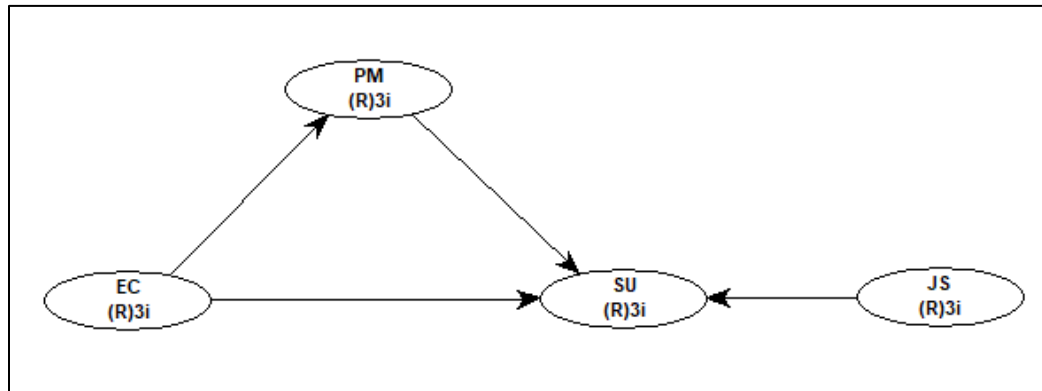
What is full latent growth?

A full latent growth analysis could be seen as a comprehensive analysis of moderating effects where the moderating variable is “latent”, in the sense that it does not “disrupt” the model in any way. This is conceptually analogous to a multi-group analysis (see, e.g., Kock, 2014). Two degrees of latent growth are provided through WarpPLS: first and second degree growth. An instance of second degree growth is equivalent to a double moderation, again with the moderating variable being “latent”; or “hidden” from the other variables in the model.

Illustrative model and data

The model in Figure 1 is used as a basis for our discussion. It contains four latent variables: the degree to which members of project teams use an e-collaboration technology (EC), the degree to which members of project teams use state-of-the-art project management techniques (PM); the business success of the projects conducted by the teams (SU); and the degree to which members of project teams are satisfied with their regular jobs (JS).

Figure 1: Illustrative model used



Notes: EC = e-collaboration technology use; PM = project management techniques use; SU = project success; JS = job satisfaction; notation under latent variable acronym describes measurement approach and number of indicators, e.g., (R)3i = reflective measurement with 3 indicators.

We created data employing the Monte Carlo simulation method (Kock, 2016); using the model above as a basis, and also using prior research on project teams involved in the development of new products in various organizations. Examples of new products would be: a new toothpaste, a new car part, and a new pill to treat a disease. The data contained 300 cases, each case referring to one project team. That is, the unit of analysis is the project team, not the individual.

The model incorporates the following expectations: that e-collaboration technology use (EC) facilitates the use of project management techniques (PM), which in turn increases project success (SU); and that e-collaboration technology use (EC) also increases project success (SU) directly, without PM mediation. Finally, the model controls for the effect of job satisfaction (JS) with respect to project success (SU).

Using full latent growth to test moderating relationships

Sometimes the actual inclusion of moderating variables and corresponding links in a model leads to problems; e.g., increases in collinearity levels, and the emergence of instances of Simpson's paradox (Kock, 2015; Kock & Gaskins, 2016). By using the menu option "Explore full latent growth", WarpPLS users can completely avoid these problems. This menu option allows users to estimate the effects of a latent variable or indicator on all of the links in a model (all at once), without actually including any links among the variable and other variables in the model. Moreover, growth in coefficients associated with links among different latent variables and between a latent variable and its indicators, can be estimated; allowing for measurement invariance tests applied to loadings and/or weights.

Figures 2 and 3 show latent growth coefficients and respective P values, which refer to a full latent growth analysis applied to our illustrative model, and where the latent growth variable is EC. The degree of latent growth chosen was first degree growth. As can be seen, this full latent growth analysis suggests a significant latent growth effect, associated with a 0.413 coefficient, of the latent variable EC on the link between the latent variables PM and SU. This is equivalent to saying that the moderating effect of EC on the link PM > SU is strong and significant, when this moderating effect is estimated in a “latent” way – i.e., without including the moderating link in the model.

Figure 2: Latent growth coefficients

Latent growth variable type

Latent variable

Latent growth variable

EC

D

F

Notes: select latent growth variable type and name, then select the degree of growth to be considered. The coefficients refer to changes in the coefficients selected (e.g., path coefficients), of the degree selected.

Latent growth coefficients				

	EC	PM	SU	JS
EC				
PM	0.028			
SU	0.356	0.413		0.107
JS				

Figure 3: P values for latent growth coefficients

P values (one-tailed)				
(most likely to be used here)				

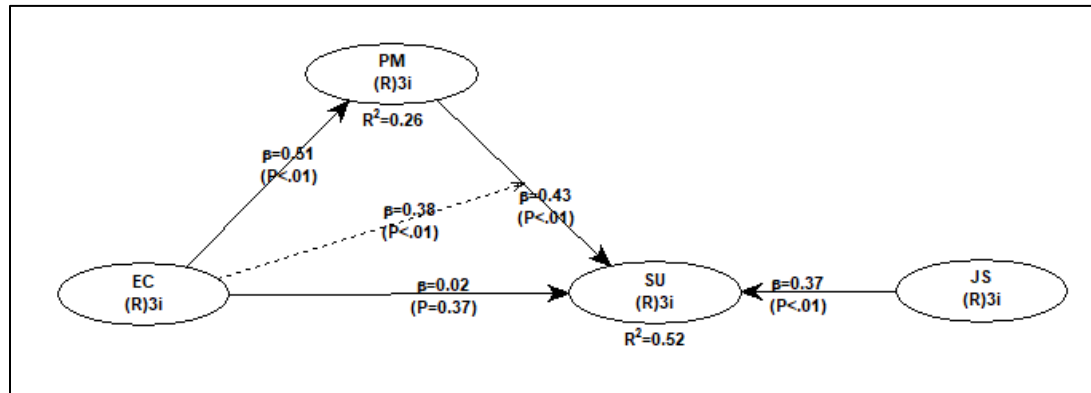
	EC	PM	SU	JS
EC				
PM	0.314			
SU	<0.001	<0.001		0.030
JS				

Note that the full latent growth analysis also shows a strong and significant relationship (coefficient of 0.356) between EC and its own link with SU. If a link, as in this case, includes the latent growth variable itself, then the corresponding latent growth coefficient, if significant, suggests the existence of a nonlinear relationship (which is also equivalent to “self-moderation”; for a discussion of this equivalence in an action research context see: Kock et al., 2017). In such an instance (i.e., when the link includes the latent growth variable itself) the level of nonlinearity is likely “Warp2” if it is associated with significant first degree growth; and likely “Warp3” if it is associated with significant second degree growth.

What if the moderating link is explicitly included in the model?

Figure 4 shows the results of an analysis where the moderating effect of EC on the link $PM > SU$ is explicitly included in the model. This means that the interaction variable $EC*PM$ is modeled by the software as a predictor of SU ; in addition to the direct predictors EC and PM . As can be seen, the moderating effect has a lower magnitude (0.380 coefficient) than the corresponding latent growth effect (0.413 coefficient).

Figure 4: Model with moderating link explicitly included



The reason for the lower magnitude of the effect when the moderating link is explicitly included in the model is that the interaction variable EC*PM controls for the direct effects of the other predictors, namely EC and PM. Since the interaction variable includes variation from each of those predictors, it is not surprising that it is somewhat correlated with them. Given this, one should expect the moderating effect to be lower than the corresponding latent growth effect. Moreover, the effects associated with the direct links EC > SU and PM > SU are also slightly reduced by the explicit inclusion of the moderating link in the model.

In this analysis, the outer model analysis algorithm used was “Factor-Based PLS Type CFM3”, and the inner model analysis algorithm used for all paths was “Linear”. Since all paths are modeled as linear, we do not capture the nonlinearity suggested by the full latent growth analysis in connection with the self-moderation link $EC > (EC > SU)$. If we set the $EC > SU$ link as “Warp2”, we do capture the nonlinearity. The path coefficient goes from 0.02 to 0.13 and becomes statistically significant.

Conclusion

A full latent growth analysis, in the context of PLS-SEM, is a comprehensive analysis of moderating effects where the moderating variable is “latent”. That is, that variable does not “disrupt” the model in any way. In this paper we illustrated a full latent growth analysis through an PLS-SEM analysis of a model with four latent variables.

Acknowledgments

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