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Testing a moderated mediation in PLS-SEM: A full latent growth approach

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Abstract

There are various techniques for separately analyzing moderation and mediation effects in partial least squares structural equation models (PLS-SEM). These individual techniques are rather straightforward and widely understood. However, valid approaches for testing more complex moderated mediation effects that are embedded together in a single model are less well understood. In this paper, we explain and illustrate one approach to such an analysis using a complex model with numerous embedded moderated mediation relationships utilizing WarpPLS, a leading PLS-SEM software tool.

Keywords: Full Latent Growth; Moderated Mediation; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

Partial least squares structural equation modeling (PLS-SEM) is a popular analytical technique to estimate empirical relationships among latent variables in a nomological network of effects. WarpPLS (Kock, 2020a) is one of the leading software tools for estimating PLS-SEM models, with many advanced features (Amora, 2021; Kock, 2020b; 2020c; 2020d; Moqbel et al., 2020; Morrow & Conger, 2021). We discuss an approach to test for multiple moderated mediation relationships embedded in PLS-SEM models without directly adding ‘artificial’ moderating variables into the model.

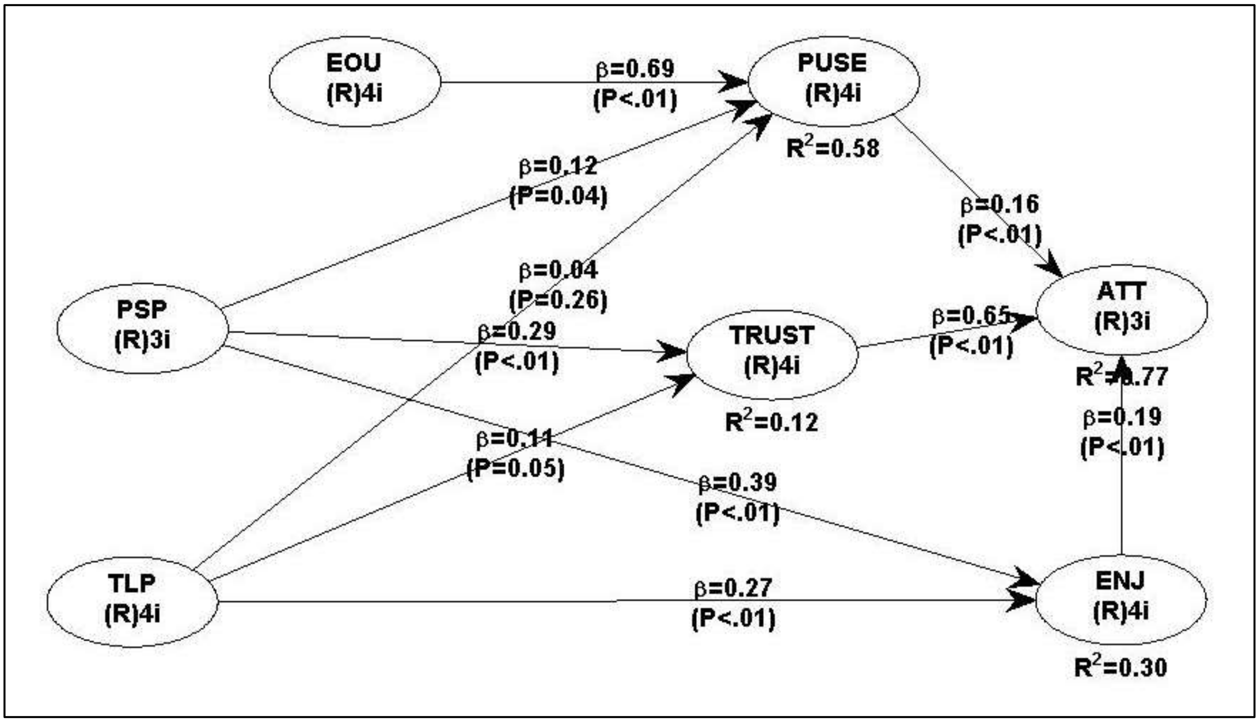
What is moderated mediation?

The term ‘moderated mediation’ gained popularity as a subset of the regression techniques known as ‘conditional process analysis’. Preceding this, Preacher & Hayes (2004) discussed tests for the significance of mediating effects using standard errors for linear relationships. Furthermore, Hayes & Preacher (2010) discussed these tests in the context of nonlinear relationships. Simply stated, ‘moderated mediation’ refers to the influence of some fourth interacting (moderating) variable affecting an existing mediated (or indirect) relationship involving at least three variables.

Illustrative model and data

The model in Figure 1 serves as a basis for our discussion. This model derives from a study by White-Baker et al. (2019), which investigated consumer attitudes and behaviors while shopping in both virtual world and non-virtual e-commerce retail environments.

Figure 1: Research model with direct effect results



Notes: EOU = perceived ease of use; PSP = perceived social presence; TLP = telepresence; PUSE = perceived usefulness; TRUST = trust; ENJ = enjoyment; ATT = attitude; notation under latent variable acronym describes measurement approach and number of indicators, e.g., (R)4i = reflective measurement with 4 indicators.

This model is appropriate because of the numerous embedded mediated relationships. There are a total of ten direct effects, indicated as individual paths from one latent variable to another. As shown in Figure 1, all ten direct effects are statistically significant (at the $P < 0.05$ level) except for the direct effect of TLP on PUSE ($\beta = 0.04$, $P = 0.26$). In addition to these ten direct effects, there are a total of three indirect (mediated) effects, including the indirect effect of: (1) EOU on ATT as mediated by PUSE; (2) PSP on ATT as mediated by PUSE, by TRUST, and by ENJ; and (3) TLP on ATT as mediated by PUSE, by TRUST, and by ENJ.

Using full latent growth to test moderating relationships

What if one wanted to explore the existence of moderating effects embedded in the model? For example, note the strong positive direct effects of both PSP ($\beta = 0.39$, $P < 0.01$) and TLP ($\beta = 0.27$, $P < 0.01$) on ENJ. The context of these variables are with respect to consumer behavior in an artificial world (e.g. Second Life). These strong positive direct effects can be interpreted as meaning that as your interactions in Second Life become less foreign, or "more real," you have greater enjoyment (ENJ) in these activities. In this context, it could be anticipated that increasing levels of perceived ease of use (EOU) would mitigate these positive effects, as greater 'ease of use' reduces the need to make the artificial world context seem "more real." Said differently, there is reason to suspect that increasing levels of EOU would negatively interact with, or moderate, the existing positive direct effects of both PSP and TLP on ENJ. However, any such moderating effects would also impinge on the indirect (mediating) effects that PSP and TLP have on ATT, as partially mediated by ENJ.

One way to approach the investigation of possible negative moderating effects of EOU on the positive direct effects from PSP on ENJ, and from TLP on ENJ would be to add two moderating links from EOU to the direct effects from: (1) PSP to ENJ; and (2) TLP to ENJ. But the inclusion of two additional moderating variables and their associated links can lead to increases in collinearity, foster "overfitting" issues, and engender instances of Simpson's paradox (Kock, 2015; Kock & Gaskins, 2016).

However, WarpPLS offers a less 'intrusive' means of estimating multiple moderated mediation effects in a model. This is basically a two-step process: (1) estimate all of the direct and mediating effects without the inclusion of any moderating variables; and then (2) use the menu option "Explore full latent growth" in WarpPLS to estimate the moderating effects of any latent variable on all of the links in a model simultaneously. To accomplish step one, WarpPLS automatically outputs estimated summary coefficients and their associated P values for all direct and mediating effects in a model.

Figure 2 shows the aggregated beta coefficients for the three indirect (mediating) effects in the model presented in Figure 1. There are significant indirect effects of: (1) TLP on ATT (β = 0.126, P = 0.025); (2) PSP on ATT (β = 0.284, P < 0.001); and EOU on ATT (β = 0.108, P = 0.009).

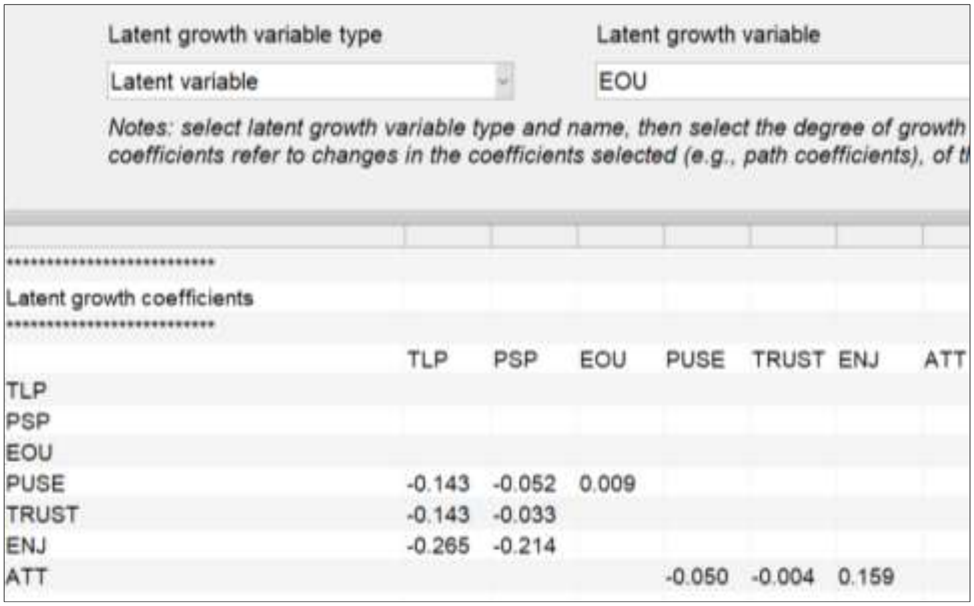
Figure 2: Indirect (mediating) effect coefficients.

Indirect effects for paths with 2 segments

	TLP	PSP	EOU	PUSE	TRUST	ENJ	ATT
TLP							
PSP							
EOU							
PUSE							
TRUST							
ENJ							
ATT	0.126	0.284	0.108				

To accomplish step two, Figure 3 shows the latent growth coefficients relating to a full latent growth analysis applied to our model, where the latent growth variable is EOU. As indicated, this full latent growth analysis suggests significant negative latent growth effects of: (1) EOU on the direct effect of PSP on ENJ (β = -0.214, P < 0.001); and (2) EOU on the direct effect of TLP on ENJ (β = -0.265, P < 0.001). This is equivalent to saying that the moderating effects of EOU on the direct effects of: (1) PSP to ENJ; and (2) TLP to ENJ are both negative and significant, when these moderating effects are estimated in a "latent" way; that is, without directly adding these moderating links into the model. However, these moderating influences also impinge on the partial mediating effects of both PSP and TLP on ATT as mediated by ENJ.

Figure 3: Latent growth coefficients


Latent growth variable type: Latent variable

Latent growth variable: EOU

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

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Latent growth coefficients

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	TLP	PSP	EOU	PUSE	TRUST	ENJ	ATT
TLP							
PSP							
EOU							
PUSE	-0.143	-0.052	0.009				
TRUST	-0.143	-0.033					
ENJ	-0.265	-0.214					
ATT				-0.050	-0.004	0.159	

The results in Figure 3 also indicate three additional moderating relationships of EOU on the direct effects of: (1) TLP on PUSE (β = -0.143, P = 0.013); (2) TLP on TRUST (β = -0.143, P = 0.013); and ENJ on ATT (β = 0.159, P = 0.006). Even if we disregard the significant moderating effect of EOU on the direct effect of TLP on PUSE since the direct effect of TLP on PUSE is not significant (β = 0.04, P = 0.26), we have still effectively discovered four significant moderating effects for just one of the variables (EOU) on the existing mediating effects in this model. Furthermore, if these four moderating variables are explicitly included in the model, there will be a cascading effect of altering all of the direct and moderating effects through the ‘artificial’ inclusion of these additional moderating variables. In this latter case, one might question the validity of all of the estimated direct and indirect path coefficients in the model as the result of adding these ‘phantom’ variables.

Conclusion

This paper presents a technique using WarpPLS to assess moderated mediation effects in complex PLS-SEM models. This can be reliably accomplished using a two-step process: (1) assess the direct and mediating effects; and then (2) assess the moderating effects using a full latent growth analysis. This approach has the benefit of not intruding and disrupting the integrity of the original model by adding ‘artificial’ moderating variables directly.

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