Convergent validity assessment in PLS-SEM: A loadings-driven approach

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Abstract

Assessment of convergent validity of latent variables is one of the steps in conducting structural equation modeling via partial least squares (PLS-SEM). In this paper, we illustrate such an assessment using a loadings-driven approach. The analysis employs WarpPLS, a leading PLS-SEM software tool.

Keywords: Convergent Validity; Partial Least Squares; Structural Equation Modeling; WarpPLS.

Introduction

Structural equation modeling employing partial least squares (PLS-SEM) is typically analyzed and interpreted sequentially, in two stages, which involve the analysis of the measurement model followed by the analysis of the structural model (Amora et al., 2016). Analysis of the measurement model includes the assessment of convergent validity, discriminant validity, and reliability (Kock, 2014).

In this paper, we illustrate the assessment of convergent validity, employing a loadings-driven approach. The illustration is carried out using WarpPLS version 7.0 (Kock, 2020a), a leading PLS-SEM software tool with many advanced features (Kock, 2020b; 2020c; 2020d; Moqbel et al., 2020; Morrow & Conger, 2021). The focus is on reflective latent variables.

What is convergent validity?

Convergent validity is a measure of the quality of a measurement instrument where the instrument itself is typically a set of question-statements (Kock, 2020a). A measurement instrument has good convergent validity if the question-statements (or other measures) associated with each latent variable are understood by the respondents in the same way as they were intended by the designers of the question-statements (Kock, 2014).

Essentially, assessment of convergent validity is an analysis of the links between question-statements and latent variables based on loadings and cross-loadings. The coefficients of the question-statements with the primary latent variable are called factor loadings or loadings while the coefficients of the question-statements with the other latent variables are called cross-loadings.

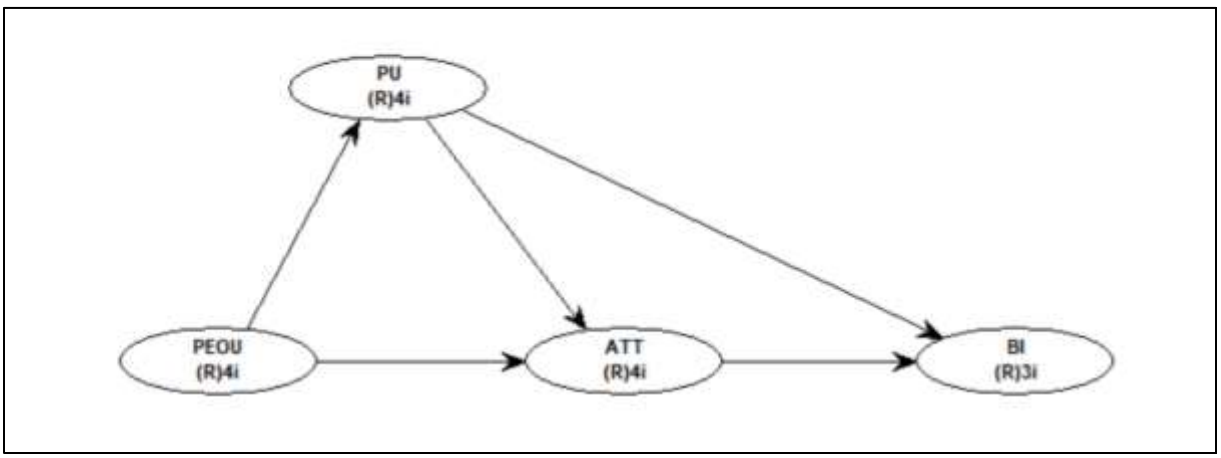
There are various variations of loadings and cross-loadings that are provided by WarpPLS when PLS-SEM is conducted, namely: combined loadings and cross-loadings, normalized combined loadings and cross-loadings, pattern loadings and cross-loadings, normalized pattern loadings and cross-loadings, structure loadings and cross-loadings, and normalized structure loadings and cross-loadings.

An illustrative example using combined loadings and cross-loadings, which have been used by most researchers, is provided in the next section. The other variants of loadings and cross-loadings are beyond the scope of this paper. See Kock (2020a) for the discussion of the other variants of loadings and cross-loadings.

Illustrative model and data

The model in Figure 1 is used as a basis for our discussion. It is part of the bigger extended technology acceptance model in Fearnley and Amora (2020), which explored the acceptance and adoption of Brightspace, a learning management system being utilized by faculty members at a private college in the Philippines. The model contains four latent variables: the perceived usefulness of the Brightspace (PU), the perceived ease of use of the Brightspace (PEOU), attitude towards using the Brightspace (ATT), and the behavioral intention to use the Brightspace (BI). All are reflective latent variables with four indicators (except BI with only 3 indicators).

Figure 1: Illustrative model used



Notes: PU = perceived usefulness of the Brightspace; PEOU = perceived ease of use of the Brightspace; ATT = attitude towards using the Brightspace; and BI = behavioral intention to use the Brightspace; notation under latent variable acronym describes measurement approach and number of indicators, e.g., (R)4i = reflective measurement with 4 indicators.

The indicators were measured using the response options ranging from 1 (strongly disagree) to 4 (strongly agree). Sample indicators or question-statements are: I intend to use the functions and content of Brightspace to assist my academic activities (BI1), I intend to use the functions and content of Brightspace as often as possible (BI2), and I intend to use the functions and content of Brightspace in the future (BI3). All are indicators of BI. The data contained 127 faculty members.

Using combined loadings and cross-loadings to assess convergent validity

Combined loadings and cross-loadings have been used by many researchers from various disciplines as basis for concluding that the measurement model has convergent validity. In the combined loadings and cross-loadings, the loadings are from a structure matrix (i.e., unrotated) while the cross-loadings are from a pattern matrix (i.e., oblique-rotated); thereby, the loadings are always within the -1 to 1 range (Kock, 2020a). For reflective latent variables, it is expected that the loadings are high and the cross-loadings are low. Two criteria are recommended as the basis for concluding that a measurement model has acceptable convergent validity: (1) the loadings should be 0.5 or higher and (2) the P values associated with the loadings should be less than .05 (Kock, 2014; 2020a). In addition, cross-loadings should be low. Indicators for which these criteria are not satisfied may be excluded in the analysis.

Figure 2 shows the WarpPLS output of the combined loadings and cross-loadings. The latent variable names (BI, PU, PEOU, ATT) are listed at the top of each column and the indicator names at the beginning of each row. As shown, the indicators for each latent variable are statistically significant (i.e., the p values are less than .05), with very high loadings (i.e., above the .50 threshold), and no cross-loadings (i.e., no large values in the other latent variables). These findings imply that all the latent variables (BI, PU, PEOU, ATT) have convergent validity.

Figure 2: Combined loadings and cross-loadings

	PEOU	PU	ATT	BI	Type (as defined)	SE	P value
PEOU1	(0.812)	0.050	0.112	0.004	Reflective	0.073	<0.001
PEOU2	(0.821)	-0.185	0.196	-0.212	Reflective	0.073	<0.001
PEOU3	(0.910)	0.249	-0.162	-0.119	Reflective	0.071	<0.001
PEOU4	(0.878)	-0.131	-0.118	0.318	Reflective	0.072	<0.001
PU1	0.090	(0.934)	-0.051	-0.086	Reflective	0.071	<0.001
PU2	-0.011	(0.944)	0.126	-0.148	Reflective	0.071	<0.001
PU3	-0.017	(0.953)	-0.015	0.027	Reflective	0.071	<0.001
PU4	-0.063	(0.916)	-0.062	0.212	Reflective	0.071	<0.001
ATT1	-0.024	0.472	(0.886)	0.168	Reflective	0.072	<0.001
ATT2	0.017	-0.190	(0.908)	0.058	Reflective	0.071	<0.001
ATT3	-0.139	-0.019	(0.906)	-0.249	Reflective	0.071	<0.001
ATT4	0.146	-0.252	(0.905)	0.026	Reflective	0.071	<0.001
BI1	0.102	0.050	-0.142	(0.939)	Reflective	0.071	<0.001
BI2	-0.123	0.084	0.237	(0.918)	Reflective	0.071	<0.001
BI3	0.018	-0.136	-0.092	(0.914)	Reflective	0.071	<0.001

Convergent validity when there is a moderating variable

For illustration purposes, a moderating link from ATT to the PU-BI relationship was added to the model (Figure 3). The moderating link represents the hypothesis that the attitude of using the Brightspace (ATT) moderates the relationship between the perceived usefulness (PU) and behavioral intention of using (BI) the Brightspace. WarpPLS 7.0 has three moderating effects calculation options: “Two Stages”, “Variable Orthogonalization”, and “Indicator Products”. The default moderating effects calculation option is the “Two Stages” approach.

This paper focuses on the "Indicator Products" approach. To shift from the "Two Stages" to the "Indicator Products" approach, go to the "View or change moderating effects settings" menu option, under the "Settings" menu option on the software's main window (Figure 4). The "Indicator Products" option employs indicator products for the creation of the interaction variable that implements the moderating effect.

Figure 3: Model with moderating link explicitly included

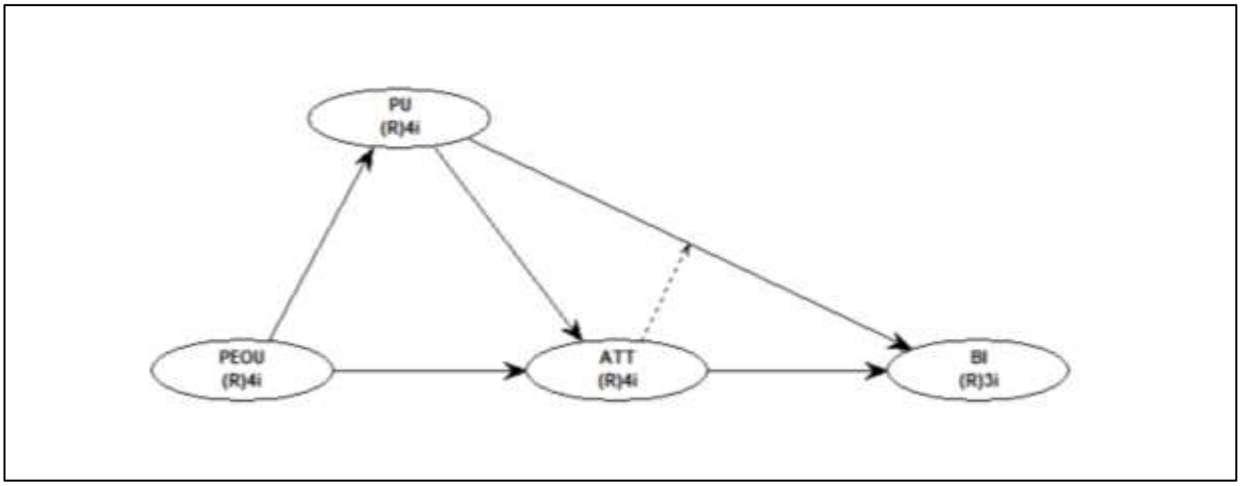


Figure 4: View or change moderating effects settings

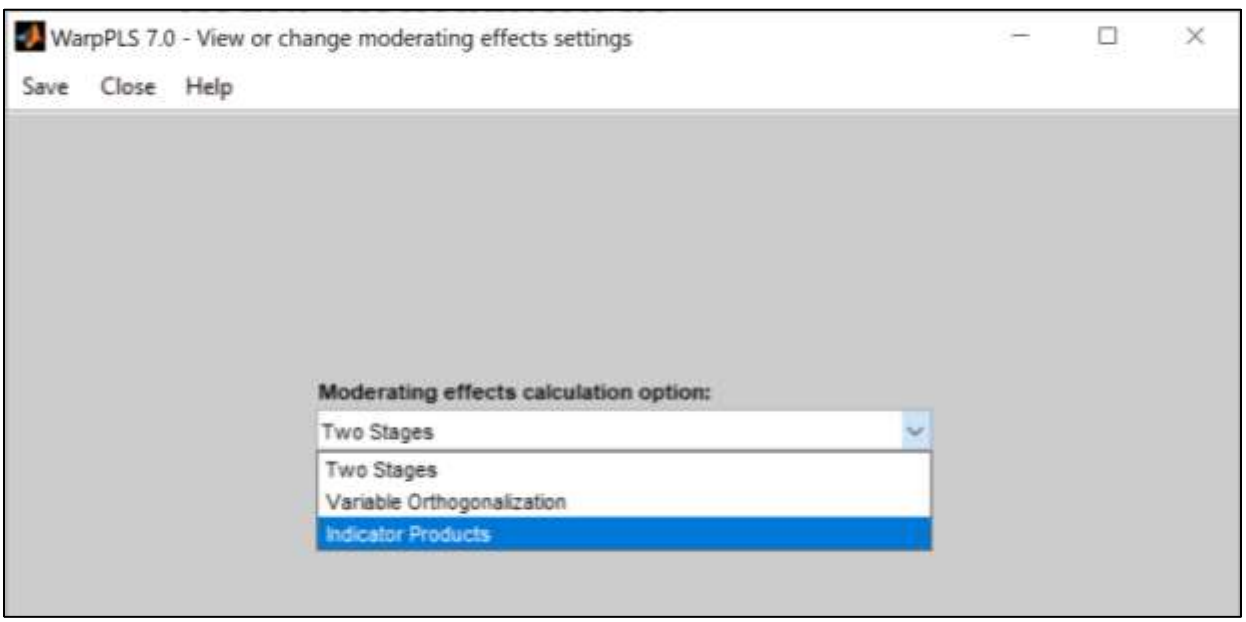


Figure 5 presents the WarpPLS results of the combined loadings and cross-loadings. As shown, additional column and rows are displayed in the table. The additional column is the product latent variable (PSE*PU) which is the moderating effect latent variable. The additional rows are the indicator products (e.g., PSE1*PU1, PSE1*PU2) which represent the indicators of the moderating effect latent variable. The loadings and cross-loadings of the moderating effect latent variable are displayed in the table.

The same criteria described in the previous section can be used in assessing the convergent validity of the moderating effect latent variable. That is, the loadings should be 0.5 or higher, the P values associated with the loadings should be less than .05, and no cross-loadings. As shown, the indicator products are statistically significant (i.e., the p values are less than .05), with very high loadings (i.e., above the .50 threshold), and no cross-loadings (i.e., no large values in the other latent variables). These findings imply that the moderating effect latent variable (PSE*PU) has convergent validity.

Figure 5: Combined loadings and cross-loadings

	PEOU	PU	ATT	BI	ATT*PU	Type (as defined)	SE	P value
ATT3	-0.135	-0.060	(0.906)	-0.267	0.010	Reflective	0.071	<0.001
ATT4	0.160	-0.286	(0.905)	0.069	-0.030	Reflective	0.071	<0.001
BI1	0.101	0.079	-0.158	(0.939)	0.027	Reflective	0.071	<0.001
BI2	-0.115	0.129	0.231	(0.918)	0.106	Reflective	0.071	<0.001
BI3	0.012	-0.211	-0.069	(0.914)	-0.134	Reflective	0.071	<0.001
ATT1*PU1	-0.013	-0.282	0.184	0.004	(0.903)	Reflective	0.071	<0.001
ATT1*PU2	0.032	-0.289	0.106	0.069	(0.897)	Reflective	0.071	<0.001
ATT1*PU3	-0.037	-0.334	0.316	-0.026	(0.901)	Reflective	0.071	<0.001
ATT1*PU4	0.046	-0.208	0.154	-0.064	(0.945)	Reflective	0.071	<0.001
ATT2*PU1	0.082	-0.110	-0.104	0.130	(0.907)	Reflective	0.071	<0.001
ATT2*PU2	0.142	-0.117	-0.232	0.189	(0.891)	Reflective	0.072	<0.001
ATT2*PU3	0.042	-0.135	0.147	0.009	(0.938)	Reflective	0.071	<0.001
ATT2*PU4	0.064	0.008	0.005	-0.064	(0.923)	Reflective	0.071	<0.001
ATT3*PU1	-0.006	0.214	-0.229	0.118	(0.945)	Reflective	0.071	<0.001
ATT3*PU2	-0.017	0.211	-0.424	0.306	(0.924)	Reflective	0.071	<0.001
ATT3*PU3	-0.035	0.196	-0.177	0.165	(0.941)	Reflective	0.071	<0.001

Conclusion

In this paper, we illustrated the convergent validity assessment in PLS-SEM through the use of the technology acceptance model with four latent variables. The assessment of the convergent validity employed a loadings-based approach. The analysis used WarpPLS, a leading PLS-SEM software tool.

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