

On the validity assessment of formative measurement models in PLS-SEM

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Abstract

Structural equation modeling via partial least squares (PLS-SEM) is the preferred approach when a research model includes formative measurement models. In this paper, the validity assessment of first-order and higher-order measurement models is illustrated using real data employing the WarpPLS, a prominent software tool for PLS-SEM.

Keywords: Structural Equation Modeling; Partial Least Squares; Formative Measurement Model; Formative Latent Variable; First-order; Higher-order; WarpPLS.

Introduction

SEM is composed of two models: the measurement model and the structural model. The measurement model describes the relationships between each latent variable and its indicators, while the structural model represents the causal relationships among the latent variables. Measurement models can be reflective or formative. In the context of PLS-SEM with reflective measurement models, the convergent validity assessment is discussed in Amora (2021) and Kock (2014), while the discriminant validity assessment is discussed in Kock (2014) and Rasoolimanesh (2022). In this paper, we illustrate the validity assessment of first-order and higher-order formative measurement models using real data with the WarpPLS software, a leading tool that supports both reflective and formative models (Amora, 2021; Canatay et al., 2022; Ezeugwa et al., 2022; Hubona & Belkhamza, 2021; Kock, 2014; Kock, 2022a, 2022b, 2022c; Ma & Zhang, 2023).

Assessing the validity of formative measurement models

PLS-SEM is the preferred approach when a research model involves formative measurement models. The indicators are the defining elements of the formative latent variable (Jarvis et al., 2003), and they are expected to measure certain attributes of the formative latent variable. According to Kock (2022c), the indicators of the formative model are not expected to be highly correlated with the latent variable score because they are not expected to be highly correlated with one another. For practical applications, the measurement model should be set as formative if the indicators are not expected to be highly correlated, even though these indicators clearly refer to the same latent variable (Kock, 2022c).

To assess the validity of the first-order formative measurement model, the following three criteria (partly discussed in Kock, 2014) should be examined: 1) The indicator variance inflation

factors (VIFs) should be 2.5 or lower; 2) The indicator weights should be statistically significant ($p < .05$) and the corresponding effect sizes (ESs) should be .02 or higher; and 3) The indicator weight-loading signs (WLS) should be positive.

Large VIF values (i.e., $VIF > 2.5$), which indicate highly correlated formative indicators, should be avoided because they can trigger misleading results. In case of large VIF values, one may consider dropping/deleting the formative indicator, merging some formative indicators, or establishing a higher-order latent variable.

The second criterion aims to ensure that each formative indicator has a contribution in forming the formative latent variable. A formative indicator with effect size of less than .02 should be considered for removal even if its indicator weight is statistically significant (Kock, 2022c). The third criterion aims to ensure that each indicator has a positive contribution to the formative latent variable (i.e., no Simpson's paradox instance). In WarpPLS, a positive WLS (i.e., $WLS=1$) indicates no Simpson's paradox instance, while a negative WLS (i.e., $WLS=-1$) indicates the existence of a Simpson's paradox instance. Note that the WLS can be used for both formative and reflective models (Kock, 2022c).

To assess the validity of the higher-order measurement model, the following three steps are recommended. Step 1: Assess the first-order measurement model. If the first-order measurement model is formative, then assess the validity by using the three criteria presented above. If the first-order measurement model is reflective, then use the criteria discussed in Amora (2021), Kock (2014) and Rasoolimanesh (2022). Step 2: Save the scores of the first-order latent variables in Step 1. Step 3: Assess the second-order measurement model. The latent scores in Step 2 serve as indicators of the second-order latent variable. If the second-order measurement model is formative, then assess the validity following the three criteria presented above. Use the criteria discussed in Amora (2021), Kock (2014) and Rasoolimanesh (2022) if the second-order measurement model is reflective.

First-order formative measurement model example: Illustrative model and data

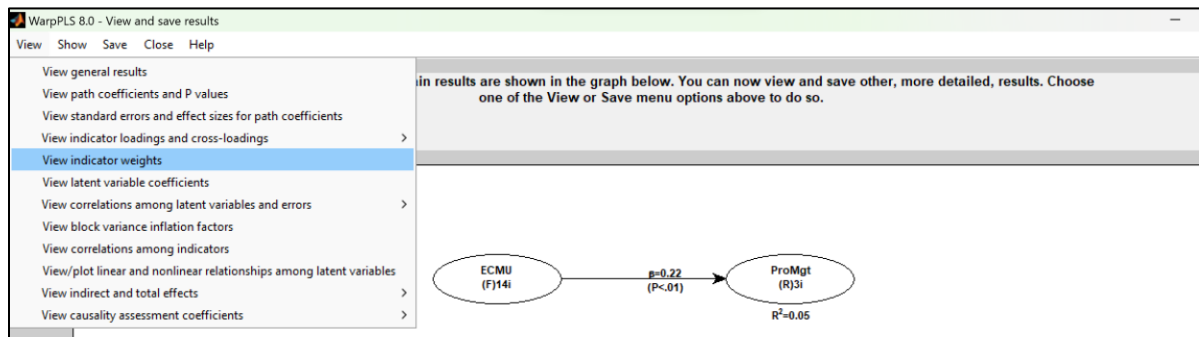
Figure 1 illustrates the model, where ECMU represents the extent to which electronic communication media were used, while ProMgt refers to the degree to which each team employed established project management techniques. ECMU is a first-order formative latent variable with a total of 14 indicators. The dataset ($n=290$) used in this study was downloaded from the WarpPLS website. The Likert-type scale was used as a measurement instrument. Sample formative indicators for ECMU include sharing electronic files (ECMFiles) and sending emails to fellow team members (ECMEmail).

First-order formative measurement model example: Assessing the validity

On the main menu, click on "View" and then select "View indicator weights" (Figure 2). WarpPLS generates a table that contains the indicator weights, P-values, VIF, WLS, and ES (Figure 3). The illustration focuses mainly on the ECMU.

Figure 1: Illustrative model for the first-order formative model example

Notes: ECMU = Electronic communication media used; (F)14i = formative measurement model with 14 indicators

Figure 2: Viewing the indicator weights and other statistics of the indicators**Figure 3: Indicator weights and other indicator statistics for the first-order formative model example**

WarpPLS 8.0 - Indicator weights

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	ECMU	ProMgt	Type (as defined)	SE	P value	VIF	WLS	ES
ECMEmaillist	(0.131)	0.000	Formative	0.058	0.012	1.389	1	0.059
ECMBoard	(0.127)	0.000	Formative	0.058	0.014	1.208	1	0.055
ECMFiles	(0.154)	0.000	Formative	0.057	0.004	1.275	1	0.081
ECMSharedWkspc	(0.153)	0.000	Formative	0.057	0.004	1.322	1	0.081
ECMNewslet	(0.148)	0.000	Formative	0.057	0.005	1.391	1	0.075
ECMAutoRout	(0.143)	0.000	Formative	0.057	0.007	1.371	1	0.071
ECMFTP	(0.165)	0.000	Formative	0.057	0.002	1.419	1	0.094
ECMWebPage	(0.136)	0.000	Formative	0.057	0.010	1.254	1	0.063
ECMVoiceMsg	(0.110)	0.000	Formative	0.058	0.029	1.393	1	0.041
ECMTeleconf	(0.130)	0.000	Formative	0.058	0.012	1.456	1	0.058
ECMVideoConf	(0.155)	0.000	Formative	0.057	0.004	1.377	1	0.083
ECMDeskVC	(0.152)	0.000	Formative	0.057	0.004	1.362	1	0.080
ECMAttachAudio	(0.146)	0.000	Formative	0.057	0.006	1.627	1	0.074
ECMAttachVideo	(0.158)	0.000	Formative	0.057	0.003	1.680	1	0.085
Prjmgt1	0.000	(0.391)	Reflective	0.055	<0.001	1.781	1	0.330
Prjmgt2	0.000	(0.410)	Reflective	0.055	<0.001	2.051	1	0.363
Prjmgt3	0.000	(0.377)	Reflective	0.055	<0.001	1.593	1	0.307

Figure 3 indicates that all 14 indicators of ECMU have VIF values below 2.5, indicating no collinearity issues. The indicator weights are significant ($p < .05$) and have effect sizes greater than .02. Additionally, all weight-loading signs are positive ($WLS=1$), indicating no Simpson's paradox instances.

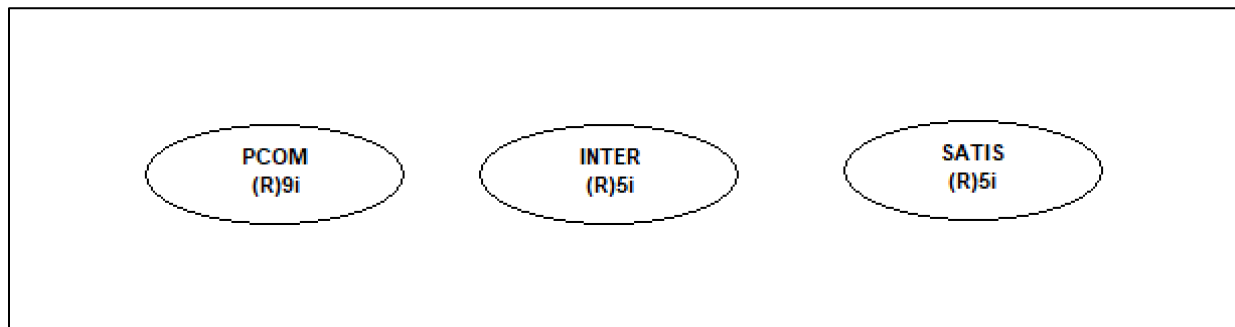
Higher-order measurement model example: Illustrative model and data

This illustrative example uses the intrinsic motivation (INMO) latent variable with three dimensions: PCOM (perceived competence/self-efficacy), INTER (interests), and SATIS (satisfaction of personal need for achievement). INMO is a higher-order measurement model with the three dimensions serving as its formative indicators. Each dimension is a first-order reflective latent variable with observed indicators that used Likert-type scale (1 to 4). The example analyzed 163 respondents.

Higher-order measurement model example: Assessment of the first-order latent variables

Figure 4 displays three reflective first-order latent variables (PCOM, INTER, and SATIS) represented by ovals without connecting arrows. The validity assessment results for these variables are not discussed here. After the validity assessment, the latent scores should be saved or added to the working dataset. To do so, select "Modify" from the main menu and then choose either "Add one or more latent variable (a.k.a factor) scores as new standardized indicators" or "Add all latent variable (a.k.a factor) scores as new standardized indicators." In this paper, the latter option is selected (see Figure 5).

Figure 4: Assessment of the three first-order latent variables



Notes: PCOM = perceived competence/self-efficacy; INTER = interests; SATIS = satisfaction of personal need for achievement.

Figure 5: Add all latent variable scores as new standardized indicators

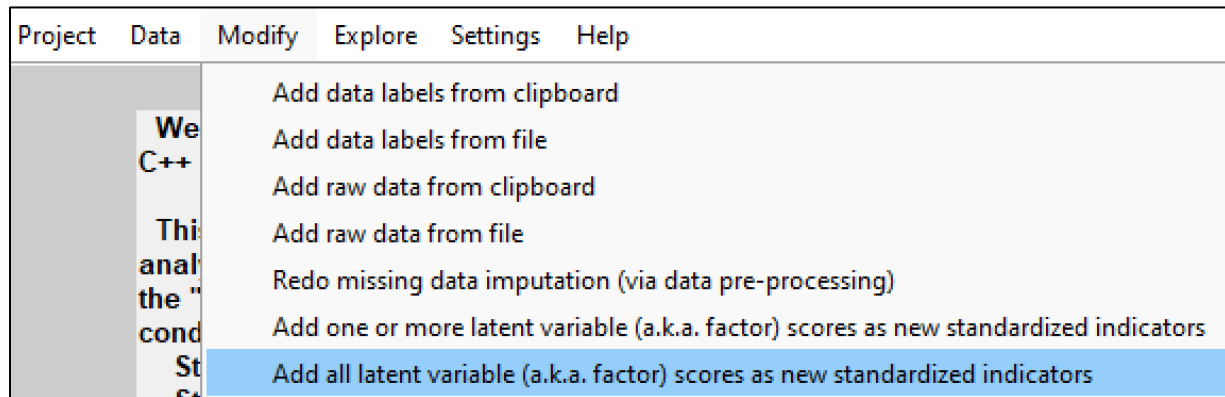


Figure 6: Viewing or saving standardized pre-processed indicator data

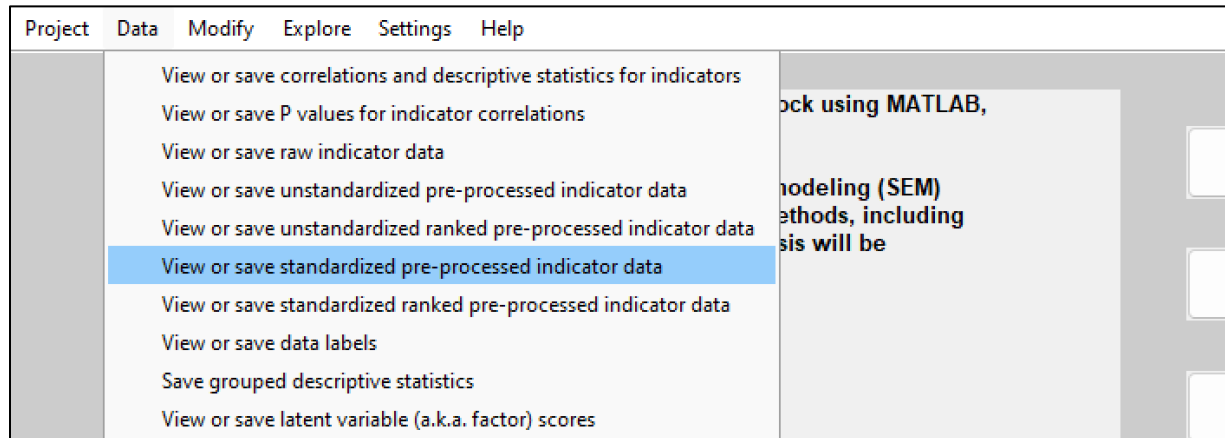


Figure 7: Dataset with the additional latent variable scores

WarpPLS 8.0 - Standardized pre-processed indicator data

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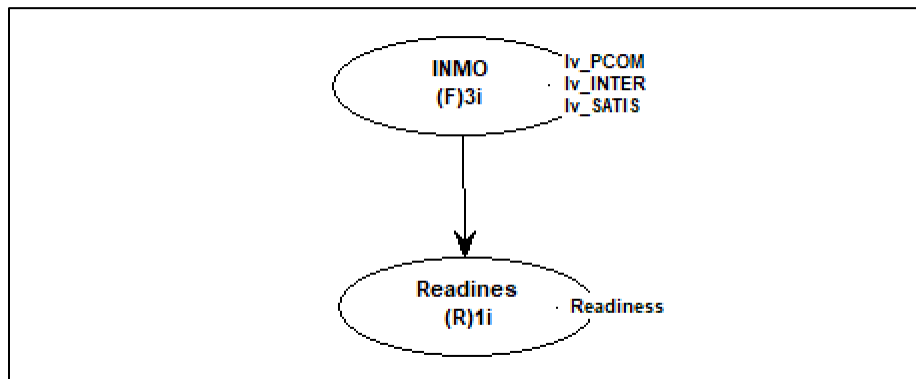
	PCOM10	PCOM11	SATIS1	SATIS2	SATIS3	SATIS4	SATIS5	Readiness	Iv_PCOM	Iv_INTER	Iv_SATIS
1	1.890	1.582	1.120	1.271	0.923	0.754	0.276	1.824	1.415	1.105	1.314
2	1.890	1.582	1.120	0.107	0.923	-0.977	-0.821	-0.226	0.393	0.176	-0.007
3	-0.351	0.280	-0.043	-1.057	0.923	-0.977	-0.821	0.799	-0.531	-0.064	-0.744
4	0.770	0.280	-0.043	1.271	0.923	0.754	0.276	1.824	1.809	0.876	0.961
5	0.770	0.280	-0.043	-1.057	-1.340	-0.977	-0.821	-0.226	-0.935	-1.018	-1.252
6	-0.351	0.280	-1.206	1.271	-1.340	0.754	1.373	-0.226	0.779	-0.305	0.430
7	0.770	0.280	1.120	1.271	-0.208	0.754	1.373	-0.226	0.877	1.105	1.391
8	-1.471	0.280	1.120	1.271	0.923	0.754	0.276	0.799	-1.274	-0.306	1.314
9	-1.471	-1.023	1.120	1.271	0.923	0.754	1.373	-0.226	-1.018	-2.426	1.644
10	-1.471	-1.023	-1.206	1.271	0.923	0.754	-0.821	-2.277	0.629	-1.729	0.277
11	-0.351	0.280	1.120	1.271	-0.208	0.754	-0.821	0.799	-0.179	1.118	0.731
12	-0.351	0.280	-1.206	-1.057	-0.208	0.754	0.276	0.799	0.711	0.647	-0.414
13	1.890	1.582	1.120	1.271	-1.340	0.754	1.373	1.824	2.636	1.575	1.137
14	-1.471	-1.023	-1.206	-1.057	-0.208	-0.977	0.276	-2.277	-1.516	-3.152	-1.022
15	0.770	0.280	1.120	-2.220	-1.340	0.754	1.373	1.824	1.065	1.575	-0.014
16	0.770	0.280	-0.043	0.107	-0.208	-0.977	0.276	0.799	0.892	0.407	-0.284

To verify that the latent scores have been successfully added to the dataset, click “Data” from the main menu and then select “View or save standardized pre-processed indicator data” (Figure 6). WarpPLS generates a table with the newly added scores, labeled as Iv_PCOM, Iv_INTER, and Iv_SATIS, which are located in the last three columns (Table 7). Be sure to save the project after adding the latent scores.

Higher-order measurement model example: Assessment of the higher-order latent variable

To assess the validity of INMO, draw a new SEM model. Click the “Proceed to Step 4” button and delete the existing ovals. Then, draw a new SEM model (Figure 8).

Figure 8: Illustrative model for the assessment of the higher-order measurement model



Notes: INMO = Intrinsic motivation with formative indicators such as Iv_PCOM, Iv_INTER, and Iv_SATIS.

Figure 9 shows that INMO is satisfactorily valid with VIF values of the three indicators below 2.5; statistically significant indicator weights (i.e., $p < .05$); no effect sizes (ES) less than .02; and all the WLS are positive (i.e., WLS=1).

Figure 9: Indicator weights and other indicator statistics for the second-order formative model

WarpPLS 8.0 - Indicator weights									
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	INMO	Readines	Type (as defined)	SE	P value	VIF	WLS	ES	
Iv_PCOM	(0.475)	0.000	Formative	0.071	<0.001	1.175	1	0.356	
Iv_INTER	(0.435)	0.000	Formative	0.071	<0.001	1.120	1	0.299	
Iv_SATIS	(0.467)	0.000	Formative	0.071	<0.001	1.165	1	0.345	
Readiness	0.000	(1.000)	Reflective	0.063	<0.001	0.000	1	1.000	

Conclusion

In this paper, the validity assessment of the first-order and higher-order measurement models with formative latent variables was illustrated using real data. The analysis was conducted using WarpPLS, a prominent software tool for PLS-SEM.

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