The Piggy in the Middle: The Role of Mediators in PLS-SEM-based Prediction

Nicholas P. Danks
The University of Dublin, Trinity College Dublin, Ireland
nicholasdanks@tcd.ie

Abstract

Partial least squares structural equation modeling (PLS-SEM) is increasingly popular as a joint explanatory predictive approach to modeling complex causal mechanisms. Researchers are becoming cognizant of the value of conducting predictive analysis using PLS-SEM for both the evaluation of overfit and to illustrate the practical value of their models. Mediators are a popular mechanism for adding nuance and greater explanatory power to such causal models. However, mediators pose a special challenge to generating predictions from PLS-SEM models as they serve a dual role of antecedent and outcome. Solutions for generating predictions from mediated PLS-SEM models have not been suitably explored or documented in the literature. Neither has there been sufficient exploration of whether the added model complexity of such mediators is justified in the light of out-of-sample predictive performance. This research note addresses that gap by formally evaluating three methods for generating predictions for mediated models and by proposing a simple metric that quantifies the predictive contribution of the mediator (PCM). We conduct monte-carlo simulations to demonstrate the efficacy of the methods under varying model conditions and then apply the methods in a model popular in the information systems literature. We find that there is no simple best solution, but that all three approaches have strengths and weaknesses. Further, the PCM metric performs well to quantify the predictive qualities of the mediator over-and-above the non-mediated alternative. We present guidelines on selecting the most appropriate method, and applying PCM for additional evidence to support research conclusions.

1. Introduction

Partial least squares structural equation modeling (PLS-SEM) has recently received great attention in the various fields of the social sciences, including information systems (Gefen et al., 2011; Ringle et al., 2012, Petter, 2018). Hair et al. (2017) conducted a literature review of two top outlets for information systems research (namely Management Information Systems Quarterly, MISQ; and Industrial Management and Data Systems, IMDS) and find that for the period 2010 to 2015 10.9 percent of empirical papers in MISQ and 13.0 percent in IMDS conduct the primary analysis using PLS-SEM.

A fundamental advantage of PLS-SEM is its ability to assess the predictive power of complex cause-effect models. The cause-effect models typically comprise several layers of constructs with multiple mediators that explain the processes through which antecedent constructs influence outcome constructs.

Generating predictions from PLS models is a recent and novel addition to the research and practice of structural equation modeling. Shmueli et al. (2016) gave us an explicit understanding of what prediction should entail in the context of PLS. That study also demonstrated how to generate predictions using the measurement indicators and structure of the model, starting with the most antecedent constructs, to predict endogenous construct scores and their measurement indicators. Subsequently, PLS has seen the inclusion of prediction in several new explanatory-predictive methods that seek to complement explanatory modeling with predictive techniques such as the Cross-validated predictive ability test (CVPAT; Liengaard et al., 2021) and predictive model selection criteria (Sharma et al., 2019; Danks et al., 2020). Furthermore, methodologists have also suggested revised model validation criteria in the light of predictive evaluation (Shmueli et al., 2019, Chin et al., 2020).

However, these methods have not sufficiently investigated the role of the mediator. The predictive assessment of mediated models poses special challenges as mediators serve as both antecedents and outcomes in PLS path models. Furthermore, the mediator has its own measurement indicators that now compete with the indicators of the antecedent in predicting outcomes. It is therefore an open question how researchers should reconcile the simultaneous predictor role of the antecedent and mediator constructs. Possible strategies for resolving this conflict have not been formally evaluated or explored in depth, researchers have little guidance on how to assess the predictive power of their mediation models in PLS-SEM.

Mediators pose an additional risk to models in that they introduce additional complexity, serving as intermediaries in causal paths. Such added complexity might contribute to model fit, at the risk of out-of-sample prediction and thus generalizability. No method for evaluating the predictive role of the mediator has been explored in the extant literature.

In this study, we set out to conceptualize each of the three solutions in greater detail and empirically validate their strengths and weaknesses using simulations. We then make use of two of these solutions to generate a metric which quantifies the predictive contribution of the mediating construct. Finally, apply the proposed methods in an empirical model salient to the information systems literature–namely the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003).

2. Mediation in PLS-SEM

Mediation occurs when the effect of an exogenous construct (X) on an outcome construct (Y) is intermediated through a third mediating construct (M). That is to say that a change in X causes a change in M which is then responsible for a change in Y. The effect of X on Y is said to be fully mediated when there is no direct effect of X on Y, but only through the mediator construct M. This is illustrated in Figure 1. An example of full mediation and the analysis thereof can be found in Ray et al. (2014) where the authors find that engagement fully mediates the influence of identity factors on prosocial intentions.

On the other hand, if X is found to have a direct effect on Y, in addition to the indirect effect via M, the effect of X on M is said to be partially mediated as illustrated in Figure 2. Dwivedi et al. (2019) conduct meta-analyses of the UTAUT model and find that behavioral intention partially mediates the relationship between facilitating conditions and use behavior.

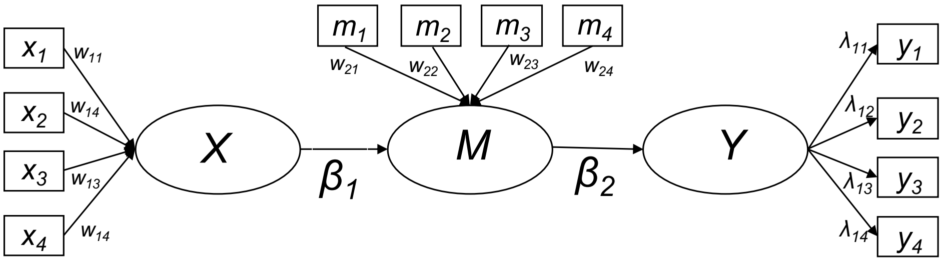


Figure 1. Fully mediated model[1]

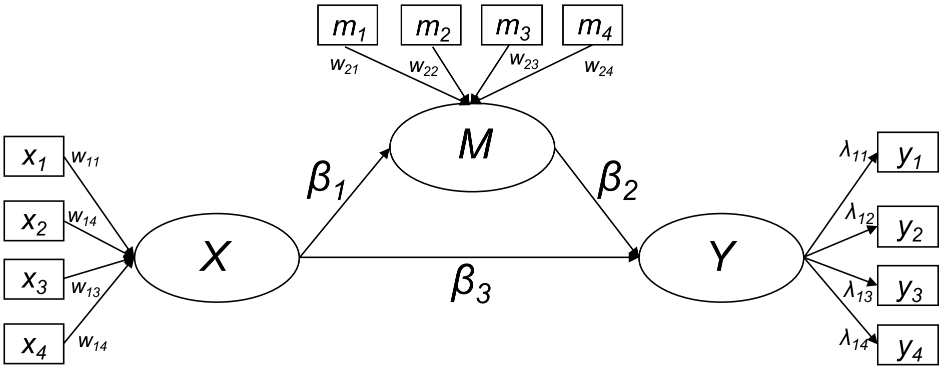


Figure 2. Partially mediated model[1]

In this research note we explore the predictive qualities of the various possible solutions for generating meaningful predictions from mediated models, and a new evaluation criterion for evaluating the predictive role of the mediator. For discussions on formal mediation testing in PLS see Hair et al. (2022), Sarstedt et al. (2020), and Nitzl et al. (2016).

[1] It is important to note that we have visualized the model in Figures 1 and 2, and Table 1, as having formative indicators for the antecedent construct X, and as having reflective indicators for the endogenous construct Y. This is done to make the description of the predictive process in Section 3 more clear. When estimating PLS models. Both a loading and a weight are estimated for every construct-indicator relationship (Shmueli et al., 2016). Thus, predictions can be generated for all the various combinations of measurement model specifications.

3. Prediction in PLS-SEM

Shmueli et al. (2016) provide an explicit algorithm for the generation of both construct-level and indicator-level predictions from PLS-SEM. Specifically, the study demonstrated how to generate predictions using the measurement indicators and structure of the model, starting with the most antecedent constructs, to predict endogenous construct scores and their measurement indicators. This process can be conceptualized for a simple model with a single antecedent construct (X) with measurement indicators x_i and single outcome construct (Y) with indicators y_i: we can use measurement weights (w_{ij}), loadings (λ_{ij}), and structural path (β) to relate the indicators of the antecedent to the indicators of the outcome.

However, if we extend this simple model by adding a mediating construct (M), we are presented with a special dilemma in that the mediator is both predictor to the outcome Y and itself the outcome of the antecedent X. Furthermore, the mediator has its own measurement indicators (m_i) that now compete with the indicators of the antecedent in predicting outcomes.

4. The Piggy in the Middle

How should one reconcile the simultaneous predictor role of the antecedent and mediating constructs? Shmueli et al. (2016) and later Danks et al. (2018) describe three alternatives to resolve this dilemma: (a) using only the earliest antecedents as indirect predictors; (b) using mediating constructs (and other direct antecedents of the outcome) as the true predictors; and (c) creating an ensemble of the first two strategies that might surpass both in predictive quality. However, neither Shmueli et al. (2016) nor Danks et al. (2018) investigate the finite sample performance of these methods or how these methods can inform theory development. Table 1 illustrates these three strategies (unused constructs, indicators, and paths are in gray).

Solution	Full Mediation	Partial Mediation

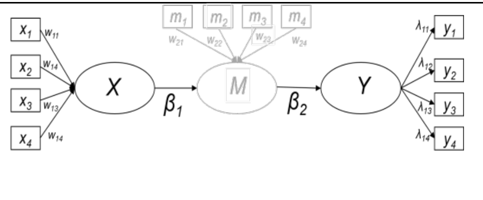
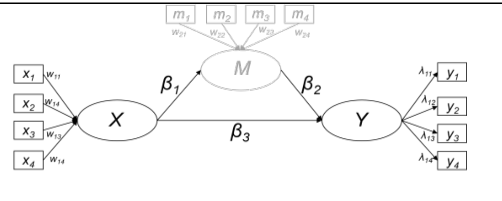
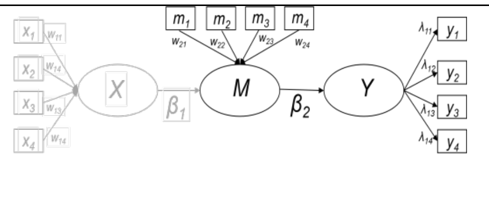
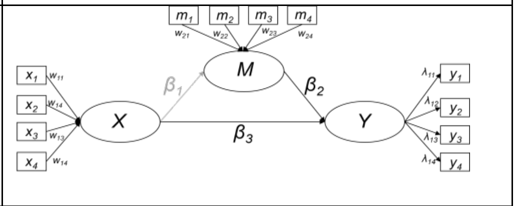
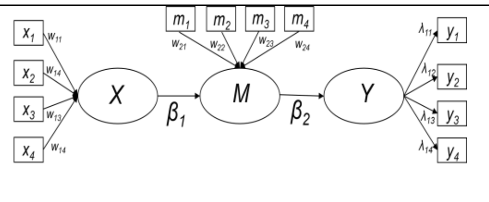
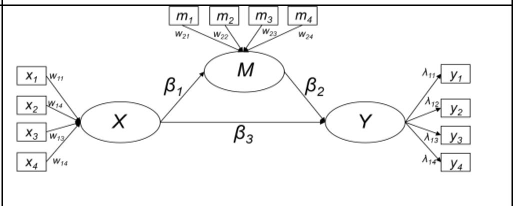
(a) Earliest Antecedents Solution		
(b) Direct Antecedents Solution		
(c) Ensemble solution		

Table 1. Illustration of the approaches to predicting in a simple mediated model[1]

We start with the first solution, wherein the earliest antecedents (EA) are used as indirect predictors. If we wish to predict the construct scores and indicators of outcome constructs, we must start with the construct scores of its mediators. But mediators are themselves the immediate outcomes of further antecedent constructs, so we can repeat this process by estimating the mediating constructs using antecedent measures and structures. This process can be repeated until we arrive at ultimate antecedent constructs, from which the prediction process can commence. In this process, the mediator is treated like piggy-in-the-middle, and its measurement indicators are bypassed in the estimation of the construct scores of the mediator and ultimately the outcome construct.

Upon reflection, we recognize that this might be a useful solution when generating outcome indicators is itself the goal, and only the indicators of the earliest antecedents are available at the given time. This approach ties in well with the goals of practitioners who need to generate predictions and forecasts for applied purposes. But because only the indirect effect of X on Y is used to predict Y and its indicators, we expect that the more distant the predictor and the outcome, the weaker the prediction. We also caution that it might be erroneous to expect the ultimately antecedent constructs to produce accurate predictions of the outcome when little of the variance of each endogenous construct is explained by its antecedents, a problem that is compounded for increasingly complex models.

The second strategy to handling mediators in PLS prediction is to use mediators as the primary predictors of endogenous constructs. This approach entails predicting outcome construct scores and indicators using only the indicators of constructs directly antecedent (DA) to the outcome construct. While the indicators of the mediator are now used in the predictive process, indicators of constructs antecedent to the mediator are not. We argue that this approach is most faithful to the structural model in that it uses only those constructs with a direct causal effect on the outcome in its prediction. In much of the theory-building literature, the mediator is set up to be of focal interest: they are the most fully examined constructs of a model because they are explained by their antecedents and in turn best explain outcomes. We note here that mediators are typically most highly correlated with the outcome constructs and explain much of their variance. And so, we expect the second solution to produce the most accurate predictions of outcome constructs and their indicators, despite omitting major portions of the theorized model. Consequently, if we have measurements of antecedent constructs at hand when making predictions, our predictions will be invariant to those antecedent indicators.

The third strategy, though only briefly alluded to by Shmueli et al. (2016), is to combine the predictions of the first two solutions to create an ensemble prediction - an approach often found in purely predictive applications. On the face of it, however, we expect that there will be little or no improvement in accuracy of the predictions generated by ensembles of PLS predictions. Ensembles are known to perform best in situations where different predictive techniques are used and there is negative, near zero, or little correlation between the predictions (Brown et al. 2001). But the two PLS predictive strategies we wish to ensemble use the same predictive technique (PLS) and their predictions should be positively correlated. Despite our pessimism, we note that even if ensembles underperform predictively in our context, they could still be useful to researchers seeking to build theory, compare models, or compare datasets. In such situations, the goal of prediction would be to include information from every part of the PLS model in the predictions, rather than purely generating accurate predictions.

5. Predictive contribution of the mediator

When hypothesizing the addition of further complexity to a model–such as a mediating construct–it is important to consider whether such additional complexity contributes not only to increased model fit quality, but also to the predictive accuracy of the model. That is, one should consider the potential of such complexity to lead to overfit. Overfit is particularly a concern in the evaluation of PLS models, which is often conducted using model fit criteria which favor overly complex models (Sharma et al. 2019). Models that are overfit suffer poor generalizability when applied to out-of-sample cases (Danks et al., 2020). Thus, it is of great importance to evaluate the out-of-sample performance of any such additions to complexity to ensure that the performance on out-of-sample prediction is commensurate with model fit.

Shmueli et al. (2016) describe such an evaluation when they propose the following regarding mediation and prediction:

> "Full mediators (such as Y1) should produce better predictions (lower out-of-sample RMSE or narrower prediction intervals) than antecedents. But if antecedents produce better-quality predictions, then researchers might want to reconsider the theoretical efficacy of their proposed mediators or acknowledge the shortcomings of their theory in terms of predictive performance. In this way, the alternative prediction schemes can be used to refine theorized models and augment traditional mediation tests such as Baron and Kenny's (1986) classical test of mediation and the Sobel test."

We propose that such a predictive evaluation of mediation should evaluate the additional predictive accuracy which is contributed to the model over-and-above the antecedent construct–as conceptualized by Shmueli et al. (2016). That is, in order to justify the addition of a mediating construct, the mediating construct should yield an improved predictive accuracy of the outcome construct. Such an evaluation should be conducted in parallel to traditional mediation testing in order to provide additional evidence for the generalizability of the mediator.

When testing for mediation, the direct path should always be estimated (Carrión, Nitzl, & Roldán, 2017; Nitzl, Roldán, & Cepeda, 2016). When conducting such mediation testing, the resultant model estimated is equivalent to the partial mediation model in column 2 of Table 1 (including only the focal antecedent, mediator, and outcome for clarity and simplicity). The EA approach when applied to such a model results in the use of the total effect of X on Y (which is equivalent to the direct effect of X on Y) in predicting Y (column 2 row 1 of Table 1). On the other hand, the DA approach makes use of both the mediator (M) and antecedent (X) constructs when predicting Y (column 2 row 2 of Table 1).

A direct comparison of the additive predictive accuracy of the model including both antecedent and mediator constructs versus the predictive accuracy of the model including the antecedent construct alone will provide an indication of the additive contribution of the mediator construct to the predictive accuracy of the model Thus, if we wish to know the contribution of the mediator to the predictive accuracy of the model on the outcome construct, we can compare the results of the DA and EA approaches applied in a partial mediation context. Such an evaluation will provide additional evidence of the predictive contribution of the mediator, rather than simply serving to increase model complexity.

We propose calculating this predictive contribution of the mediator (PCM) by first taking the difference of the out-of-sample predictive metrics (such as RMSE, or MAE, Shmueli et al., 2019) calculated for each of the DA and EA approaches (equation 1). This simple difference would vary greatly depending on the magnitude of the predictive metrics analyzed and the scale of the underlying data and thus might be difficult to interpret across models. Thus, we recommend that difference then be divided by the predictive metric for the EA approach to yield a percentage (equation 2). The resultant percentage then represents the increase in predictive accuracy due to the addition of the mediator.

$$\Delta METRIC = METRIC_{EA} - METRIC_{DA} \quad (1)$$

$$PCM = \frac{\Delta METRIC}{METRIC_{EA}} \quad (2)$$

We recommend the use of cross-validated predictive metrics such as RMSE and MAE as described by Shmueli et al. (2019) in calculating PCM. Since it is formulated as a percentage, this metric should have a range approximately from -1 to 1, with a negative value indicating that the mediator has damaged the predictive accuracy of the model on the outcome construct and a positive value indicating that the mediator has a positive impact on the predictive accuracy of the outcome construct. In the context of a more complex model (such as the UTAUT model), with multiple additional antecedents to the focal outcome the predictive contribution of the mediator might be attenuated. Thus, we recommend conducting the estimation of PCM on the focal mediation model in isolation. It is not initially clear what constitutes a low, moderate, or high value for the PCM metric, and thus we conduct a monte-carlo simulation to explore the performance of the metric.

6. Monte-carlo simulations

6.1. Simulation experiment I

6.1.1. Design, data, and estimation

To investigate the performance of these three solutions and the PCM metric, we conducted a monte-carlo simulation in the R statistical environment (R Core Team, 2021). We specify three structural models, one fully mediated, one partially mediated (see Table 1), and a third model excluding the mediator and specifying only a direct effect of the antecedent construct (X) on the outcome (Y). All constructs are specified as having reflective measurement models. Using these three structural models, we manipulated the following experimental conditions, which correspond to the conditions commonly encountered in applied research (e.g., Hair, Hollingsworth, et al., 2017; Nitzl, 2016; Ringle et al., 2020):

• Four conditions of sample size (100, 200, 300, and 500),

• Five conditions of effect sizes on the structural paths (0.1, 0.2, 0.3, 0.4, and 0.5),

• Three indicator loading patterns with different levels of average variance extracted (AVE): – High AVE with loadings: (0.9, 0.9, 0.9, and 0.9), – Moderate AVE with loadings: (0.8, 0.8, 0.8, and 0.8), and – Low AVE with loadings: (0.7, 0.7, 0.7, and 0.7),

• Three conditions of simulated mediation (full, partial, and no).

The data were generated using Schlittgen's procedure available in the cbsem package for the R statistical software (Schlittgen, 2019). Specifically, we generate 1,800 simulated datasets for each of the fully mediated, partially mediated, and no mediation models. We then apply the three proposed predictive strategies for a model with mediator described in Table 1 and conduct the estimation and prediction using the SEMinR package in R (Ray et al., 2021). We calculate the out-of-sample RMSE for each method across the simulation factors, as well as PCM, and evaluate the predictive performance.

6.1.2. Results

Data generation type	**Full mediated model**		**Partial mediated model**		**Ensemble prediction**	**Direct effect model**
	DA	**EA**	**DA**	**EA**		
Full mediation	**1050 (58.3%)**	195 (10.8%)	183 (10.2%)	16 (1.5%)	305 (16.9%)	51 (2.8%)
Partial mediation	104 (5.8%)	96 (5.3%)	**1187 (65.9%)**	49 (2.7%)	274 (15.2%)	90 (5%)
No mediation	59 (3.3%)	154 (8.6%)	225 (12.5%)	493 (27.4%)	302 (16.8%)	**567 (31.5%)**

Table 2. Number of times the approach generates the highest predictive accuracy in terms of out-of-sample RMSE.

Notes: Bolded values show the method with highest accuracy across mediation and model types. The first column distinguishes between the data simulated to contain a fully mediated relationship, partially mediated relationship, or no mediated relationship.

Data generation type	**Full mediated model**		**Partial mediated model**		**Ensemble prediction**	**Direct effect model**	**Correlation DA vs EA**
	DA	**EA**	**DA**	**EA**			
Full mediation	**0.973**	0.997	0.976	1.000	0.983	1.001	0.91

Partial mediation	0.938	0.963	**0.905**	0.938	0.921	0.938	0.77
No mediation	1.008	1.002	0.977	0.974	0.982	**0.974**	0.29

Table 3. Average RMSE for the approach

Notes: Bolded values show the method with highest accuracy across mediation and model types. The first column distinguishes between the data simulated to contain a fully mediated relationship, partially mediated relationship, or no mediated relationship.

The results demonstrate that the direct-antecedents solution generates predictions with the highest accuracy for both full and partial mediation (58.3% and 65.9% respectively), far beyond the ensemble solution (16.9% and 15.2% respectively), and the earliest-antecedents solution (10.8% and 2.7%) as illustrated in Table 2. When no mediation is present, that is there is only a direct effect of X on Y, then unsurprisingly the direct effect model generates the highest levels of predictive accuracy (31.5%). These results are mirrored by the mean RMSEs reported in Table 3.

The ensemble approach consistently outperforms the EA approach, but fails to improve upon the DA approach. As predicted, this is due to the high correlation between the predictions generated by the DA and EA approaches ($\rho=0.77$ and $\rho=0.91$ for partial and full mediation respectively).

An interesting result to note is that the RMSE yielded by the EA approach in the partial mediation model is almost identical to that yielded by the direct effect model for all three simulated mediation types. This is because the EA approach when applied to the case of partial mediation is in essence the total effect of X on Y and neglects any contribution by the mediating construct. This reinforces our formulation of the PCM as the difference between EA and DA approaches (equation 1).

Data generation type	**PCM positive**	**PCM negative**
Full mediation	1477 (82.1%)	323 (17.9%)
Partial mediation	1497 (83.2%)	303 (16.8%)
No mediation	356 (19.8%)	1444 (80.2%)

Table 4. Number of times the PCM is positive indicating improved predictive power of mediated model in terms of out-of-sample RMSE.

Data generation type	Descriptive Statistics						
	Min	1st Quartile (25%)	Median (50%)	Mean	3rd Quartile (75%)	90th Percentile	Max
Full mediation	-0.049	0.003	0.021	0.031	0.049	0.064	0.219
Partial mediation	-0.044	0.004	0.025	0.038	0.059	0.102	0.219
No mediation	-0.058	-0.006	-0.002	-0.003	-0.006	0.002	0.042

Table 5. Descriptive statistics describing the PCM ratio performance on the simulated data in terms of out-of-sample RMSE.

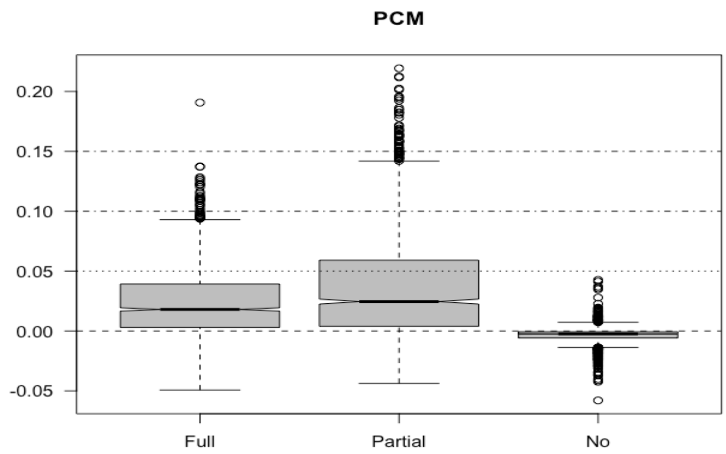


Figure 3. Distribution of the PCM metric on Full mediation, Partial mediation, and No mediation conditions of simulation

The simulation brings to light some indications of the performance of the PCM metric on evaluating the predictive contributions of the mediator in Tables 4 and 5. The PCM metric is positive indicating additional predictive contribution of the mediator over-and-above the antecedent construct in more than 80% of the cases in which mediation was designed in the data generation model. Similarly, the PCM metric is negative indicating no additional predictive contribution of the mediator in over 80% of the cases in which no mediation was designed in the data generation model. These results indicate that the metric is robust at identifying when the mediator has predictive contribution.

We further analyze the distribution of the metric under the various mediation conditions in the data generation model – partial mediation, full mediation, and no mediation (Table 5). Under conditions of mediation (partial and full), the PCM metric ranges from approximately 0 to 0.05 for the lower 75% of cases. Indicating that a value of 0 to 0.05 represents that mediation is present, and the mediator has a mild contribution to predictive accuracy. The PCM metric ranges from 0.05 to 0.10 in the 75th to 90th percentile of the partially mediated models. This represents a strong contribution to predictive power by the mediator. After this point, the two distributions diverge, but we expect that a PCM value of greater than 0.10 (90th percentile for partial mediation) should represent a strong contribution to predictive power by the mediator. The PCM distributions under the three data generation models can be inspected in figure 3.

6.2. Simulation Experiment II

6.2.1. Design, data, and estimation

Next, we investigate the performance of PCM metric by means of a further monte-carlo simulation in the R statistical environment (R Core Team, 2021). From the perspective of this simulation, we wish to explore the values that the PCM metric can take under varying levels of strength of mediation.

The Variance Accounted For (VAF) is often used to determine the proportion of the mediation effect (Hair et al., 2014). This criterion is not without criticism but can be seen as a "rule-of-thumb" when describing the size of the mediation effect (Ramayah et al., 2018). A VAF value of less than 0.2 is seen as indicating no mediation, a value larger than 0.2 but less than 0.8 as indicating partial mediation, and value greater than 0.8 as indicating full mediation (Ramayah et al., 2018).

We use this a base from which to describe varying levels of mediation, however we believe that the absolute magnitude of the paths plays a greater role than the proportion of indirect to total effects. Thus, we specify five conditions of effect size that relate to mediation size–specifically we allocate values to β_1, β_2, and β_3 such that the mediation in the data generation model indicates VAF of 0.1, 0.3, 0.5, 0.7, 0.9 respectively. Additionally, we include a sixth condition of effect size with a higher direct effect of 0.3 to inspect how the magnitude of the path effects the PCM metric.

We now only specify a partially mediated (see Table 1) data generation model and commensurate with simulation experiment I. All constructs are specified as having reflective measurement models. We manipulated the following experimental conditions, which correspond to the conditions commonly encountered in applied research:

- Four conditions of sample size (100, 200, 300, and 500),
- Six conditions of effect sizes on the structural paths:

Condition	β_1	β_2	β_3	VAF
1	0.1	0.1	0.09	0.10
2	0.23	0.23	0.1	0.31
3	0.32	0.32	0.1	0.51
4	0.6	0.6	0.15	0.71
5	0.6	0.6	0.05	0.88
6*	0.6	0.6	0.3	0.55

Table 6. Six conditions of effect sizes and resultant VAF

- Three indicator loading patterns with different levels of average variance extracted (AVE): – High AVE with loadings: (0.9, 0.9, 0.9, and 0.9), – Moderate AVE with loadings: (0.8, 0.8, 0.8, and 0.8), and – Low AVE with loadings: (0.7, 0.7, 0.7, and 0.7).

The data were generated using Schlittgen's procedure available in the cbsem package for the R statistical software (Schlittgen, 2019). Specifically, we generate 2,160 simulated datasets. We then apply the proposed approach for calculating PCM, and evaluate the performance of the PCM metric. We conduct the estimation and prediction using the SEMinR package in R (Ray et al., 2021).

6.2.2. Results

The simulation provides further evidence of the performance of the PCM metric on evaluating the predictive contributions of the mediator. When inspecting the boxplots in Figure 4 there is a clear positive relationship between VAF and PCM. We find that the PCM metric increases with an increase in VAF, but is also directly related to the absolute magnitude of the paths.

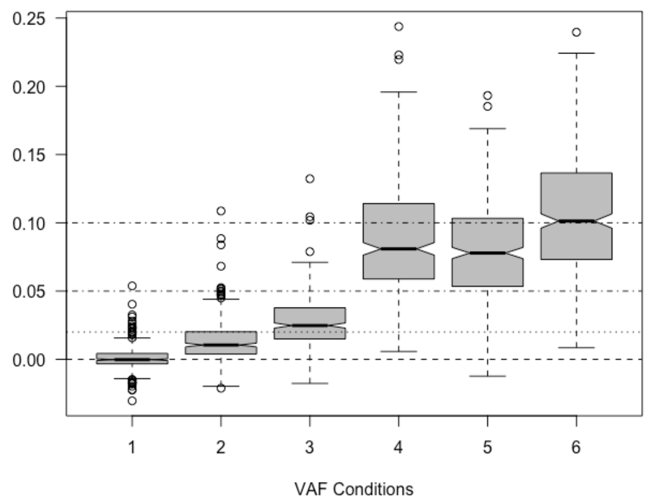


Figure 4. Distribution of the PCM metric on varying conditions of VAF

The approximate boundaries of 0 – 0.5 for small, 0.05 – 0.1 for moderate, and greater than 0.1 for strong predictive contribution of the mediator can be observed in the results of these simulations (Figure 4). These findings are supported by the descriptive statistics of these simulation conditions in Table 7, providing further evidence for this rule-of-thumb for evaluating the predictive contribution of the mediator. We now apply the three approaches to generating predictions from mediated models and the proposed PCM metric to an extant example from the literature.

Simulated VAF condition	Descriptive Statistics						
	Min	1st Quartile (25%)	Median (50%)	Mean	3rd Quartile (75%)	90th Percentile	Max

1: 0.1	-0.030	-0.003	-0.000	0.001	0.004	0.011	0.054
2: 0.3	-0.021	0.004	0.010	0.013	0.020	0.032	0.109
3: 0.5	-0.018	0.015	0.0248	0.027	0.038	0.051	0.132
4: 0.7	0.006	0.059	0.081	0.086	0.114	0.133	0.244
5: 0.9	-0.012	0.054	0.078	0.079	0.103	0.125	0.193
6*: 0.55 higher β_3	0.008	0.073	0.101	0.106	0.137	0.164	0.240

Table 7. Descriptive statistics describing the PCM ratio performance on the simulated data in terms of out-of-sample RMSE.

7. Empirical example

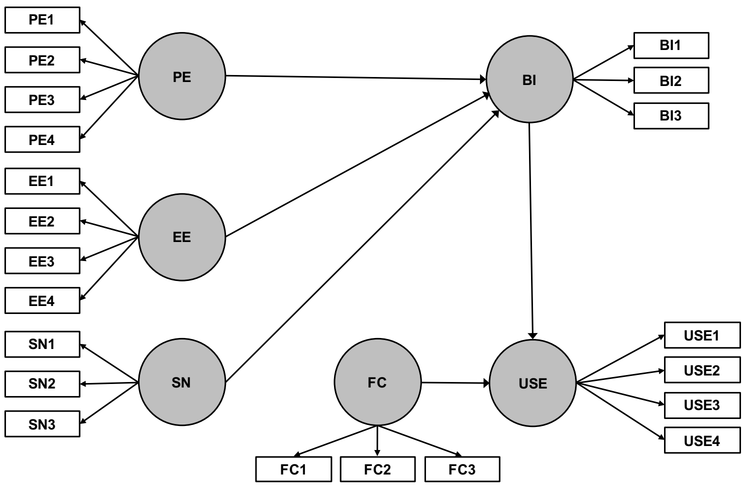


Figure 5. Empirical example conceptual model

In our empirical example we will compare the application of these approaches and the PCM metric to a well-established and widely used model from the information systems literature–the unified theory of acceptance and use of technology (Venkatesh, 2003). Specifically, we use the data and model of Al-Gahtani et al. (2007). Figure 5 illustrates the conceptual model of the empirical demonstration. The primary antecedent constructs are Performance Expectancy (PE), Effort Expectancy (EE), Social Norms (SN), and Facilitating Conditions (FC) which collectively explain the Behavioral Intention (BI) and ultimately the Use (USE) of the software. The model includes three mediated paths: (1) PE via BI to USE, (2) EE via BI to USE, and (3) SN via BI to USE. According to the original study, these three paths are modeled (and by implication hypothesized) as fully mediated paths.

We employed the SEMinR package (Ray et al., 2021) to both estimate and generate predictions from the PLS-SEM model in the R statistical Environment (R Core Team, 2021). The estimated model meets the criteria necessary to validate a PLS-SEM model (Hair et al. 2020, Henseler et al. 2016). We will not discuss these validations in detail but will instead proceed directly to the results generated by applying the EA, DA, and ensemble predictive approaches to the model.

First, we consider the general model evaluation criteria for predictive model assessment as described by Shmueli et al. (2019). We focus our attention on the indicators of the USE construct as our focal construct of interest. The reason is two-fold. First, analyzing the predictions of the indicators of USE allows us to make a direct comparison between the predictions generated by the EA approach (which would use the Earliest Antecedent constructs PE, EE, SN, and FC to predict USE) and the DA approach (which would use only the direct antecedent constructs BI and FC to predict USE). Second, USE is the construct of primary interest to practitioners seeking to make useful and actionable predictions from such PLS-SEM models.

We first compare the prediction errors from the three techniques and find that the three methods generate highly comparable distributions of prediction errors (figure 6). Generally, the ensemble approach falls somewhere between the EA and DA approaches in the error distribution echoing our results in the monte-carlo simulation.

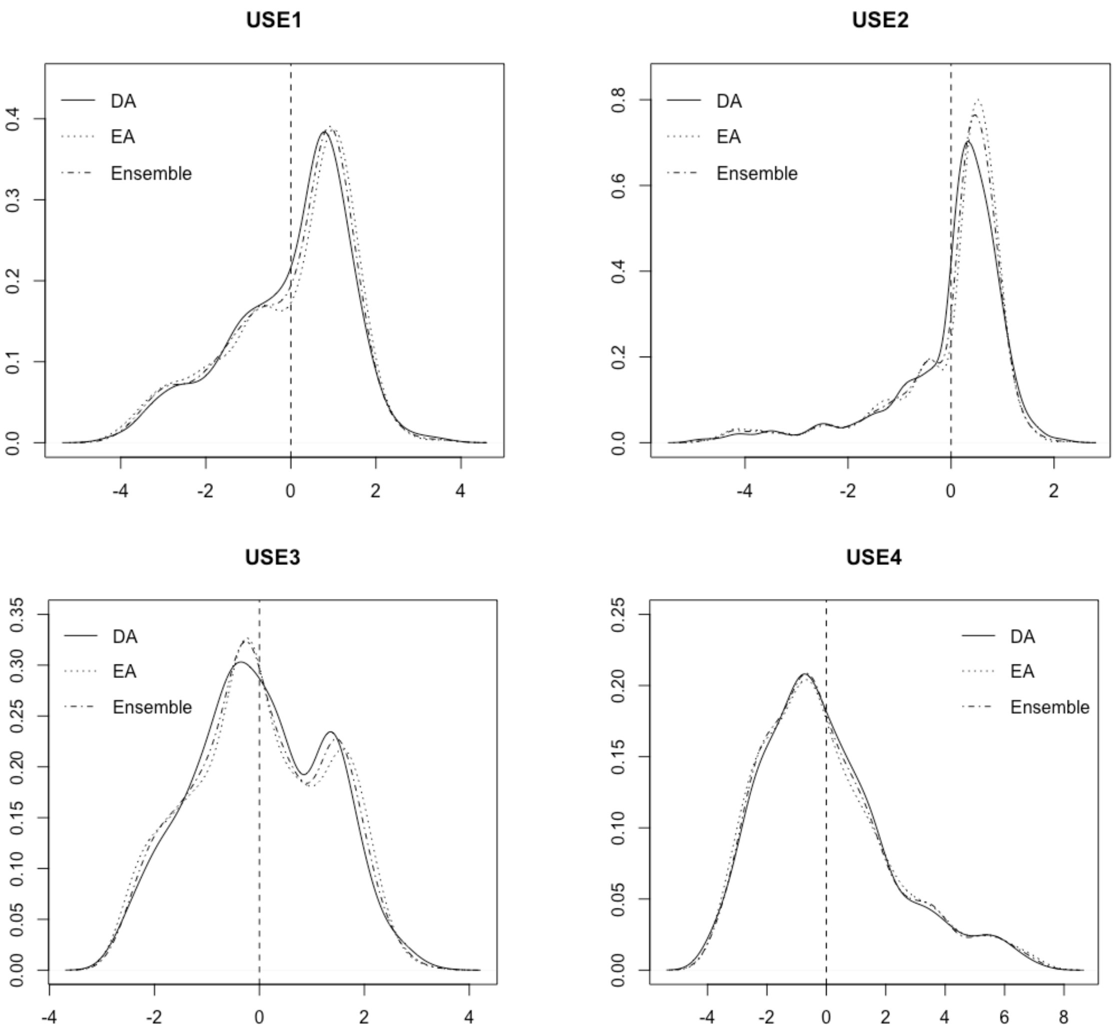


Figure 6. Distribution of out-of-sample prediction residuals generated from competing approaches for USE1, USE2, USE3, and USE4

Next, we consider the prediction metrics generated by the three metrics – we primarily consider RMSE but include MAE in addition as the distributions of prediction error are non-symmetrical (Shmueli et al., 2019).

Indicator	**DA Approach**		**EA Approach**		**Ensemble Approach**	
	RMSE	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
USE1	1.409	1.145	1.481	1.234	1.436	1.184
USE2	1.127	0.788	1.161	0.841	1.137	0.812
USE3	1.253	1.036	1.295	1.070	1.266	1.047
USE4	2.201	1.720	2.257	1.775	2.220	1.738

Table 8. Results from three approaches

When considering the predictive metrics from the three approaches, it is clear that the DA approach consistently performs the best in terms of predictive power. In addition, the

Ensemble approach seems to average the better DA prediction and worse EA prediction to generate results somewhere between the two.

We now consider the predictive contribution of the three mediators (PE, EE, and SN) in terms of the PCM metric. We thus isolate the three focal mediation relationships (visualized in Table 9) and estimate the PCM for each of the indicators USE1, USE2, USE3, and USE4 (Table 10).

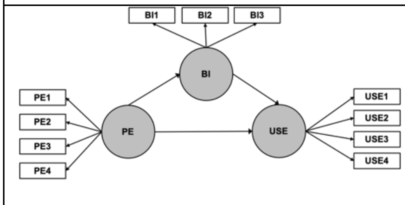
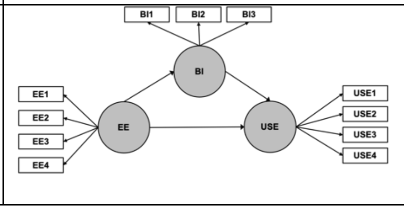
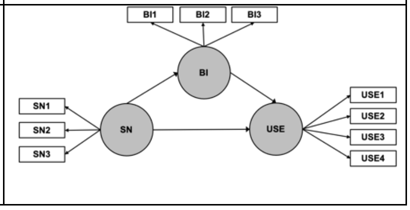
PE	EE	SN
		

Table 9. Models for the estimation of PCM for empirical example

Indicator	PE PCM	Conclusion	EE PCM	Conclusion	SN PCM	Conclusion
USE1	0.080	Moderate	0.068	Moderate	0.096	Moderate
USE2	0.054	Moderate	0.046	Weak	0.069	Moderate
USE3	0.059	Moderate	0.045	Weak	0.087	Moderate
USE4	0.039	Weak	0.039	Weak	0.070	Moderate

Table 10. PCM results for empirical example

We estimate PCM of 0.080, 0.054, 0.059, and 0.039 for USE1, USE2, USE3, and USE4 respectively, in the context of the mediated path of PE via BI to USE. These PCM values are largely moderate, and we thus conclude that BI has an overall moderate improvement of predictive power when considering this mediation relationship. Similarly, we calculate PCM of 0.068, 0.046, 0.045, 0.039 for USE1, USE2, USE3, and USE4 respectively, in the context of the mediated path of EE via BI to USE. These values fall within the weak category and thus we conclude that BI has an overall weak improvement of predictive power when considering this mediation relationship.

Interestingly, when we analyze the mediated effect of SN via BI on USE, we find that the PCM estimates are higher at 0.096, 0.069, 0.087, and 0.070 for USE1, USE2, USE3, and USE4 respectively. These values fall firmly within the strong category and suggest that there might be more to this relationship than full mediation. Our re-estimation of the model (Appendix B) finds that for this dataset, SN indeed has an indirect effect on USE. However, we caution that it is important to re-consider the hypotheses underlying the model–such a partial mediation might not make sense from a theoretical perspective. It is important, however, to note that the PCM metric gave evidence to support such a finding from a data-driven perspective.

The results from this empirical study confirm those observed in the monte-carlo experiment and provide little evidence for employing either the EA or ensemble approaches when the goal of the model is to maximize predictive accuracy. However, the PCM metric performs well in providing additional post-hoc evidence to support the generalizability of a mediation relationship after traditional mediation testing has been applied.

7. Conclusion

7.1. Discussion

This research note investigated the performance of three proposed solutions for generating predictions from PLS-SEM models and provided a predictive method for providing evidence of the generalizability of a mediated relationship. We developed a variety of simulations in the R statistical environment, generated three structural models, one fully mediated, one partially mediated (see Table 1), and a non-mediated model, considered different predictive approaches for models of varying complexity. In addition to simulated data using Schlittgen's (2019) method, we tested the relative performance of the three solutions and the PCM metric on actual likert data collected from an empirical study.

Our findings suggest that many of our expectations and concerns are valid. For example, the overwhelming predictive superiority of the direct-antecedents solution that we expected was verified by both the monte-carlo simulation and empirical example. We find that the direct antecedents solution generates predictions with the highest accuracy, well beyond both the ensemble and earliest-antecedents solutions. Overall, we demonstrated that although alternative strategies exist to incorporating mediators in PLS prediction, and although each strategy has its role in research and practice, that their predictive qualities differ greatly.

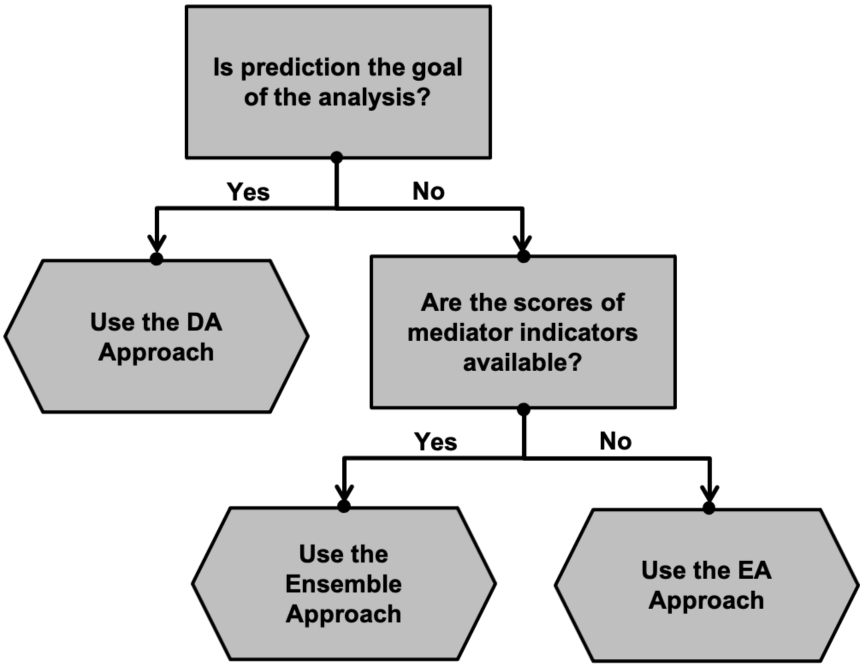


Figure 5. Decision tree for selecting the prediction approach

When the goal of PLS-SEM modeling is generating predictions or maximizing accuracy of predictions, then researchers would be best served by using the DA approach. However, if predictions were sought for a model for which mediating construct indicator data were not available, the EA approach would prove highly suitable. An example of such is when archival data is used to generate predictions in a mediated model, but no data was collected for the hypothesized mediator at that time. When researchers wish to omit no portion of the model and generate predictions that take into account all indicators and weights, then they would be best suited by the Ensemble approach.

We demonstrated that the PCM metric can be used to provide additional evidence as to whether the added complexity of a mediation relationship in a PLS model is justified by the predictive performance. We suggest that researchers routinely conduct such an analysis in parallel to traditional mediation testing in order to present evidence of predictive validity of mediated relationships. High levels of predictive validity would reassure researchers and practitioners alike that results could generalize to further datasets and potentially similar contexts, and increase confidence in the inferential findings.

7.2. Limitations and further research

We suggest that future researchers pay particular attention to the ensemble strategy, which offers a fruitful direction for theory building, despite its predictive nature differing greatly from its use in purely predictive disciplines where it originates. In particular, we suspect that ensemble predictions might yield greater advantages when disparate methods are used – such as a linear model or regression tree. An alternative might be to seek some weighting scheme that might yield an optimal combination of EA and DA predictions.

We acknowledge that our proposed initial rule-of-thumb for classifying the predictive contribution of the mediator as weak, moderate, or strong has not been sufficiently tested. We suggest that researchers publish the results of their PCM analysis, and that through meta-analysis the rules-of-thumb for this metric can be refined in later research. We additionally suggest that the PCM be re-evaluated considering the effect size for mediation proposed by Lachowicz et al. (2018). This is a particularly promising line of research.

Predictive validation of mediating constructs might have relevance to the broader topic of external validation of construct measures in a nomological network in PLS-SEM (Hair, Howard, & Nitzl, 2020). We believe that more investigation in this field of research might yield promising results.

References

Al-Gahtani, S. S., Hubona, G. S., & Wang, J. (2007). Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT. Information & management, 44(8), 681-691.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of personality and social psychology, 51(6), 1173.

Brown, G., and Xin, Y. On the effectiveness of negative correlation learning. Proceedings of first UK workshop on computational intelligence. 2001.

Carrión, G. C., Nitzl, C., & Roldán, J. L. (2017). Mediation analyses in partial least squares structural equation modeling: Guidelines and empirical examples. In H. Latan & R. Noonan (Eds.), Partial Least Squares Path Modeling (pp. 173-195). Heidelberg: Springer.

Chin, W., Cheah, J. H., Liu, Y., Ting, H., Lim, X. J., & Cham, T. H. (2020). Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. Industrial Management & Data Systems.

Danks, N. and Ray, S. (2018), Predictions from partial least squares models, in Ali, F., Rasoolimanesh, S.M. and Cobanoglu, C. (Eds), Applying Partial Least Squares in Tourism and Hospitality Research, Emerald Publishing Limited, Bingley, pp. 35-52.

Danks, N. P., Sharma, P. N., & Sarstedt, M. (2020). Model selection uncertainty and multimodel inference in partial least squares structural equation modeling (PLS-SEM). Journal of Business Research, 113, 13-24.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 21(3), 719-734.

Gefen D, Straub DW, and Rigdon EE (2011) An update and extension to sem guidelines for administrative and social science research. *MIS Quarterly* 35(2).

Hair, J. F., Hult. G. T. M., Ringle, C. M., Sarstedt, M. (2014). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks: Sage, p. 224.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*.

Hair, J. F., Howard, M., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. Journal of Business Research, 109, 101-110.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd edition). Thousand Oaks: Sage

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. Industrial management & data systems.

Lachowicz, M. J., Preacher, K. J., & Kelley, K. (2018). A novel measure of effect size for mediation analysis. Psychological Methods, 23(2), 244.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, Yet Forsaken? Introducing a Cross-Validated Predictive Ability Test in Partial Least Squares Path Modeling. Decision Sciences, 52(2), 362-392

Nitzl, C. (2016). The use of partial least squares structural equation modelling (PLS-SEM) in management accounting research: Directions for future theory development. Journal of Accounting Literature, 37, 19-35.

Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation Analyses in Partial Least Squares Structural Equation Modeling: Helping Researchers to Discuss More Sophisticated Models. Industrial Management & Data Systems, 116(9), 1849-1864.

Petter, S. (2018). Haters Gonna hate: PLS and information systems research. ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 49(2), 10-13

R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/

Ramayah, T., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3.0: An Updated Guide and Practical Guide to Statistical Analysis (2nd ed.). Kuala Lumpur, Malaysia: Pearson.

Ray, S., Kim, S. S., & Morris, J. G. (2014). The central role of engagement in online communities. Information Systems Research, 25(3), 528-546.

Ray, S., Danks, N.P., & Calero Valdez, A. (2021). seminr: Building and Estimating Structural Equation Models. R package version 2.1.0. https://CRAN.R-project.org/package=seminr

Ringle CM, Sarstedt M, and Straub D (2012) A critical look at the use of PLS-SEM in MIS Quarterly. MIS Quarterly 36(1).

Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research (in press) International Journal of Human Resource Management. https://doi.org/10.1080/09585192.2017.1416655.

Sarstedt, M., Hair Jr, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2020). Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses!. International Journal of Market Research, 62(3), 288-299.

Schlittgen, R. (2019). cbsem: Simulation, estimation and segmentation of composite based structural equation models. R package version 1.0.0. Available at: https://cran. r-project.org/web/packages/cbsem/index.html (accessed February 14, 2020).

Sharma, P., Sarstedt, M., Shmueli, G., Kim, K. H., & Thiele, K. O. (2019). PLS-based model selection: The role of alternative explanations in information systems research. Journal of the Association for Information Systems, 20(4), 4.

Sharma, P. N., Shmueli, G., Sarstedt, M., Danks, N., & Ray, S. (2019). Prediction-oriented model selection in partial least squares path modeling. Decision Sciences

Shmueli, G., Ray, S., Estrada, J. M. V., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. Journal of Business Research, 69(10), 4552-4564.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Appendix A

Code to replicate the Empirical Example

```
library(seminr)
data <- read.csv(file = "UTAUT-722.csv")
meas_model <- constructs(
  composite("PE",  multi_items("PE", 1:4), weights = mode_A),
  composite("EE",  multi_items("EE", 1:4), weights = mode_A),
  composite("SN", multi_items("SN", 1:3), weights = mode_A),
  composite("FC", multi_items("FC", 1:3), weights = mode_A),
  composite("BI", multi_items("BI", 1:3), weights = mode_A),
  composite("USE", multi_items("USE", 1:4), weights = mode_A)
)
struc_model <- relationships(
  paths(from = c("PE", "EE", "SN"), to = "BI"),
  paths(from = c("FC", "BI"), to = "USE")
)
utaut_model <- estimate_pls(data,
                            measurement_model = meas_model,
                            structural_model = struc_model)
sum_utaut_model <- summary(utaut_model)
utaut_DA <- predict_pls(utaut_model,
                        technique = predict_DA,
                        noFolds = 10,
                        reps = 10)
utaut_EA <- predict_pls(utaut_model,
                        technique = predict_EA,
                        noFolds = 10,
                        reps = 10)

sum_utaut_DA <- summary(utaut_DA)
sum_utaut_EA <- summary(utaut_EA)
sum_utaut_DA
sum_utaut_EA
ensemble_USE1 <- (utaut_DA$PLS_out_of_sample_residuals[,"USE1"] +
utaut_EA$PLS_out_of_sample_residuals[,"USE1"])/2
ensemble_USE2 <- (utaut_DA$PLS_out_of_sample_residuals[,"USE2"] +
utaut_EA$PLS_out_of_sample_residuals[,"USE2"])/2
ensemble_USE3 <- (utaut_DA$PLS_out_of_sample_residuals[,"USE3"] +
utaut_EA$PLS_out_of_sample_residuals[,"USE3"])/2
```

```
ensemble_USE4 <- (utaut_DA$PLS_out_of_sample_residuals[,"USE4"] +
utaut_EA$PLS_out_of_sample_residuals[,"USE4"])/2


plot(density(utaut_DA$PLS_out_of_sample_residuals[,"USE1"]),
     main = "USE1", lwd = 1, ylim = c(0, 0.45))
abline(v = c(0),lty = 2)
lines(density(utaut_EA$PLS_out_of_sample_residuals[,"USE1"]),
      lwd = 1, lty = 3)
lines(density(ensemble_USE1), lwd = 1, lty = 4)
legend("topleft",
       legend = c("DA", "EA", "Ensemble"),
       lwd = c(1,1,1),
       lty = c(1,3,4),
       bty = "n",
       text.col = "black",
       horiz = F )

plot(density(utaut_DA$PLS_out_of_sample_residuals[,"USE2"]),
     main = "USE2", lwd = 1, ylim = c(0,0.85))
abline(v = c(0),lty = 2)
lines(density(utaut_EA$PLS_out_of_sample_residuals[,"USE2"]),
      lwd = 1, lty = 3)
lines(density(ensemble_USE2), lwd = 1, lty = 4)
legend("topleft",
       legend = c("DA", "EA", "Ensemble"),
       lwd = c(1,1,1),
       lty = c(1,3,4),
       bty = "n",
       text.col = "black",
       horiz = F )

plot(density(utaut_DA$PLS_out_of_sample_residuals[,"USE3"]),
     main = "USE3", lwd = 1, ylim = c(0,0.35))
abline(v = c(0),lty = 2)
lines(density(utaut_EA$PLS_out_of_sample_residuals[,"USE3"]),
      lwd = 1, lty = 3)
lines(density(ensemble_USE3), lwd = 1, lty = 4)
legend("topleft",
       legend = c("DA", "EA", "Ensemble"),
       lwd = c(1,1,1),
```

```
       lty = c(1,3,4),
       bty = "n",
       text.col = "black",
       horiz = F )

plot(density(utaut_DA$PLS_out_of_sample_residuals[,"USE4"]),
     main = "USE4", lwd = 1, ylim = c(0,0.25))
abline(v = c(0),lty = 2)
lines(density(utaut_EA$PLS_out_of_sample_residuals[,"USE4"]),
      lwd = 1, lty = 3)
lines(density(ensemble_USE4), lwd = 1, lty = 4)
legend("topright",
       legend = c("DA", "EA", "Ensemble"),
       lwd = c(1,1,1),
       lty = c(1,3,4),
       bty = "n",
       text.col = "black",
       horiz = F )

ensemble_use1_rmse <- sqrt(mean(ensemble_USE1^2))
ensemble_use1_mae <- mean(abs(ensemble_USE1))
ensemble_use2_rmse <- sqrt(mean(ensemble_USE2^2))
ensemble_use2_mae <- mean(abs(ensemble_USE2))
ensemble_use3_rmse <- sqrt(mean(ensemble_USE3^2))
ensemble_use3_mae <- mean(abs(ensemble_USE3))
ensemble_use4_rmse <- sqrt(mean(ensemble_USE4^2))
ensemble_use4_mae <- mean(abs(ensemble_USE4))

## PCM metric
## Mediator 1 PE
utaut_data <- read.csv(file = "UTAUT-722.csv")



meas_model <- constructs(
  composite("PE",  multi_items("PE", 1:4), weights = mode_A),
  composite("EE",  multi_items("EE", 1:4), weights = mode_A),
  composite("SN", multi_items("SN", 1:3), weights = mode_A),
  composite("FC", multi_items("FC", 1:3), weights = mode_A),
  composite("BI", multi_items("BI", 1:3), weights = mode_A),
```

```
  composite("USE", multi_items("USE", 1:4), weights = mode_A)
)

struc_model <- relationships(
  paths(from = c("PE"), to = c("BI", "USE")),
  paths(from = c("BI"), to = "USE")
)

utaut_model <- estimate_pls(utaut_data,
                            measurement_model = meas_model,
                            structural_model = struc_model)

utaut_DA <- predict_pls(utaut_model,
                        technique = predict_DA,
                        noFolds = 10,
                        reps = 10)

utaut_EA <- predict_pls(utaut_model,
                        technique = predict_EA,
                        noFolds = 10,
                        reps = 10)

sum_utaut_DA <- summary(utaut_DA)
sum_utaut_EA <- summary(utaut_EA)

(sum_utaut_EA$PLS_out_of_sample[1,4:7] -
sum_utaut_DA$PLS_out_of_sample[1,4:7])/sum_utaut_EA$PLS_out_of_sample[1,4:7]

## Mediator 2 EE
struc_model <- relationships(
  paths(from = c("EE"), to = c("BI", "USE")),
  paths(from = c("BI"), to = "USE")
)

utaut_model <- estimate_pls(utaut_data,
                            measurement_model = meas_model,
                            structural_model = struc_model)

utaut_DA <- predict_pls(utaut_model,
                        technique = predict_DA,
```

```
                        noFolds = 10,
                        reps = 10)

utaut_EA <- predict_pls(utaut_model,
                        technique = predict_EA,
                        noFolds = 10,
                        reps = 10)

sum_utaut_DA <- summary(utaut_DA)
sum_utaut_EA <- summary(utaut_EA)

(sum_utaut_EA$PLS_out_of_sample[1,4:7] -
sum_utaut_DA$PLS_out_of_sample[1,4:7])/sum_utaut_EA$PLS_out_of_sample[1,4:7]


## Mediator 3 SN
struc_model <- relationships(
  paths(from = c("SN"), to = c("BI", "USE")),
  paths(from = c("BI"), to = "USE")
)

utaut_model <- estimate_pls(utaut_data,
                            measurement_model = meas_model,
                            structural_model = struc_model)

utaut_DA <- predict_pls(utaut_model,
                        technique = predict_DA,
                        noFolds = 10,
                        reps = 10)

utaut_EA <- predict_pls(utaut_model,
                        technique = predict_EA,
                        noFolds = 10,
                        reps = 10)

sum_utaut_DA <- summary(utaut_DA)
sum_utaut_EA <- summary(utaut_EA)

(sum_utaut_EA$PLS_out_of_sample[1,4:7] -
sum_utaut_DA$PLS_out_of_sample[1,4:7])/sum_utaut_EA$PLS_out_of_sample[1,4:7]
```

Appendix B

We first estimate the Al-Gahtani et al. (2007) model excluding direct relationships to demonstrate that we have reproduced the findings from Figure 3 in Al-Gahtani et al. (2007). These results are shown in Table B1.

Exogenous	Endogenous	
	BI	**USE**
PE	0.214*	-
EE	0.363*	-
SN	0.208*	-
FC	-	0.199*
BI	-	0.376*
R^2	0.353	0.251

Table B1. Original Al-Gahtani et al. (2007) estimates excluding direct effects

Note: * Significant at P < 0.001

We then turn to the evaluation of the mediated relationships PE, EE, and SN via BI on USE. We re-estimate the Al-Gahtani et al. (2007) model including the direct effects of PE, EE, and SN on USE (Table B2). We find that according to the criteria set out by Nitzl et al. (2016) and find that the relationships of both PE and EE on USE are fully mediated, while SN displays competitive mediation as evidenced by the significant and negative path of SN on USE.

Exogenous	Endogenous	
	BI	**USE**
PE	0.214*	-0.008^{NS}
EE	0.363*	0.032^{NS}
SN	0.208*	-0.173*
FC	-	0.207*
BI	-	0.422*
R^2	0.353	0.278

Table B2. Original Al-Gahtani et al. (2007) estimates including direct effects

Note: * Significant at P < 0.001, NS not significant at P > 0.10