

Using WarpPLS in e-Collaboration Studies: Mediating Effects, Control and Second Order Variables, and Algorithm Choices

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ABSTRACT

This is a follow-up on two previous articles on WarpPLS and e-collaboration. The first discussed the five main steps through which a variance-based nonlinear structural equation modeling analysis could be conducted with the software WarpPLS (Kock, 2010b). The second covered specific features related to grouped descriptive statistics, viewing and changing analysis algorithm and resampling settings, and viewing and saving various results (Kock, 2011). This and the previous articles use data from the same e-collaboration study as a basis for the discussion of important WarpPLS features. Unlike the previous articles, the focus here is on a brief discussion of more advanced issues, such as: testing the significance of mediating effects, including control variables in an analysis, using second order latent variables, choosing the right warping algorithm, and using bootstrapping and jackknifing in combination.

Keywords: Multivariate Statistics, Nonlinear Analysis, Partial Least Squares, Structural Equation Modeling, Virtual Teams, WarpPLS

INTRODUCTION

This article is a follow-up on two previous articles on the use of WarpPLS in e-collaboration studies, and can be seen as the third of a set of related articles. The first article in the series discusses the five main steps through which a nonlinear structural equation modeling (SEM) analysis could be conducted with the software WarpPLS (Kock, 2010b). The second article in the series discusses specific features related to grouped descriptive statistics, viewing and changing analysis algorithm and resampling

settings, and viewing and saving various results (Kock, 2011).

This and the previous articles focus on version 1.0 of the software, and use data from the same e-collaboration study as a basis for the discussion of important WarpPLS features. While the articles use an e-collaboration study as a basis, the discussions are very generic and apply to areas unrelated to e-collaboration. In fact, the discussions are pertinent to research in many different fields. At the time of this writing, published examples of the use of WarpPLS existed in marketing, management, finance, accounting, anthropology, psychology, and nursing.

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Unlike the two previous articles in the three-article set, the focus here is on a brief discussion of more advanced issues, such as: testing the significance of mediating effects, including control variables in an analysis, using second order latent variables, choosing the right warping algorithm, and using bootstrapping and jackknifing in combination.

THE E-COLLABORATION STUDY

Several screen snapshots and composites are used here to illustrate important WarpPLS features. These snapshots and composites were generated based on a study of e-collaboration in virtual teams. Overall, 209 teams were studied. The teams carried out product innovation and development tasks in a variety of economic industries and sectors. The study focused on five main latent variables, referred to here as “ECU”, “ECUVar”, “Proc”, “Effi”, and “Effe”.

“ECU” and “ECUVar” are technology-related variables. “ECU” refers to the extent to which electronic communication media, in addition to face-to-face communication, were used by each team. “ECUVar” refers to the variety of different electronic communication media used by each team, or the number of electronic communication media with different features (e.g., e-mail, teleconferencing, telephone) used by each team.

“Proc”, “Effi”, and “Effe” are non-technology-related variables. “Proc” refers to the degree to which each team employed established project management techniques, referred to in the study as “procedural structuring” techniques, hence the name of the variable. “Effi” refers to the efficiency of each team, in terms of task completion cost and time, assessed against previously planned task completion cost and time. “Effe” refers to the effectiveness of each team (a team can be effective but not efficient, and vice-versa), in terms of the actual commercial success of the new goods or services that each team developed.

TESTING THE SIGNIFICANCE OF MEDIATING EFFECTS

Using WarpPLS, one can test the significance of a mediating effect of a variable M, which is hypothesized to mediate the relationship between two other variables X and Y, by using Baron and Kenny’s (1986) criteria. The procedure is outlined below. It can be easily adapted to test multiple mediating effects, and more complex mediating effects (e.g., with multiple mediators). Please note that we are not referring to moderating effects here; these can be tested directly with WarpPLS, by adding moderating links to a model.

First two models must be built. The first model should have X pointing at Y, without M being included in the model. (You can have the variable in the WarpPLS model, but there should be no links from or to it.) The second model should have X pointing at Y, X pointing at M, and M pointing at Y. This is a “triangle”-looking model. A WarpPLS analysis must be conducted with both models, which may be saved in two different project files; this analysis may use linear or nonlinear analysis algorithms. The mediating effect will be significant if the three following criteria are met:

- In the first model, the path between X and Y is significant (e.g., $P < 0.05$, if this is the significance level used).
- In the second model, the path between X and M is significant.
- In the second model, the path between M and Y is significant.

Note that, in the second model, the path between M and Y controls for the effect of X. That is the way it should be. Also note that the effect of X on Y in the second model is irrelevant for this mediation significance test. Nevertheless, if the effect of X on Y in the second model is insignificant (i.e., indistinguishable from zero, statistically speaking), one can say that the case is one of “perfect” mediation. On the other hand, if the effect of X on Y in the second model is significant, one can say that

Figure 1(a). First WarpPLS model in a mediating effect significance test

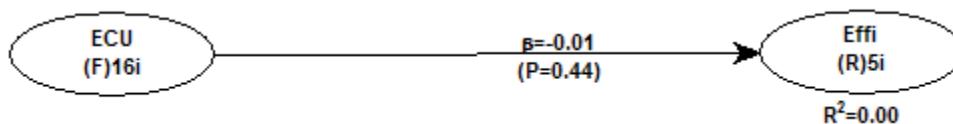
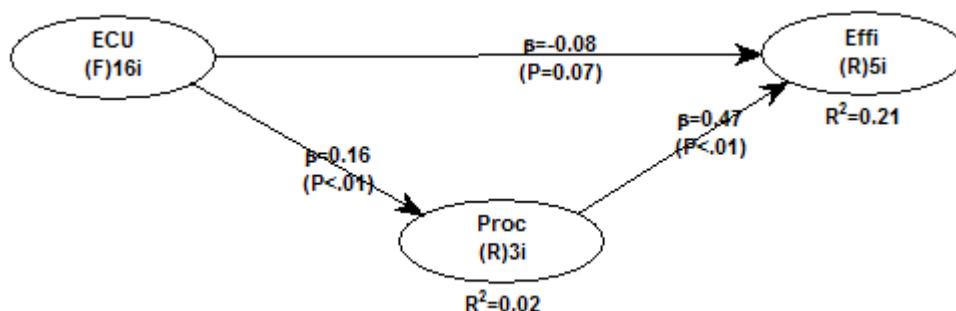


Figure 1(b). Second WarpPLS model in a mediating effect significance test



the case is one of “partial” mediation. This of course assumes that the three criteria are met. Generally, the lower the effect of X on Y in the second model, the more “perfect” the mediation is, if the three criteria for mediating effect significance are met.

Figures 1(a) and 1(b) show two models created for a mediating effect significance test. The mediating variable is “Proc”; the degree to which each team in our sample e-collaboration study employed established project management techniques. These techniques are referred to in the study as procedural structuring techniques. The effect that is hypothesized to be mediated by “Proc” is that between “ECU” and “Effi”. “ECU” refers to the extent to which electronic communication media were used by each team. “Effi” refers to the efficiency of each team, in terms of task completion cost and time.

In this case, the mediating effect of “Proc” is *not* significant, because the first of the three criteria is not met. That is, in the first model, the path between “ECU” and “Effi” is not significant (beta = -.01, P = 0.44).

The conclusion above is reached even though the two other criteria are met. In the

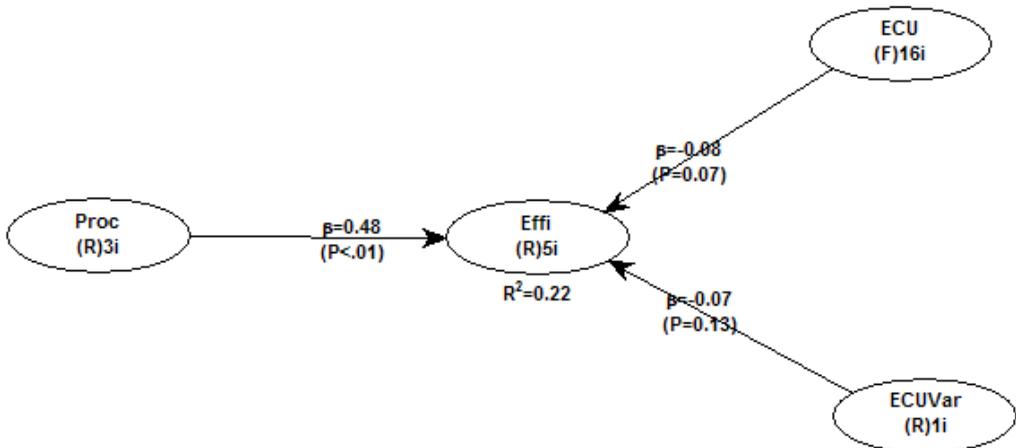
second model, the path between “ECU” and “Proc” is significant (beta = .16, P < .01), and the path between “Proc” and “Effi” is also significant (beta = .47, P < .01).

INCLUDING CONTROL VARIABLES IN AN SEM ANALYSIS

As part of an SEM analysis using WarpPLS, a researcher may want to control for the effects of one or more variables. This is typically the case with what are called “demographic variables”, or variables that measure attributes of a given unit of analysis that are (usually) not expected to influence the results of the SEM analysis.

For example, let us assume that one wants to assess the effect of a technology, whose intensity of use is measured by a latent variable T, on a behavioral variable measured by B. The unit of analysis for B is the individual user; that is, each row in the dataset refers to an individual user of the technology. The researcher hypothesizes that the association between T and B is significant, so a direct link between T and B is included in the model.

Figure 2. Including control variables in an SEM analysis



If the researcher wants to control for age (A) and gender (G), which have also been collected for each individual, in relation to B, all that is needed is to include the variables A and G in the model, with direct links pointing at B. No hypotheses are made. For that to work, gender (G) has to be included in the dataset as a numeric variable. For example, the gender “male” may be replaced with 1 and “female” with 2, in which case the variable G will essentially measure the “degree of femaleness” of each individual.

After the analysis is conducted, let us assume that the path coefficient between T and B is found to be statistically significant, with the variables A and G included in the model as described above. In this case, the researcher can say that the association between T and B is significant, “regardless of A and G” or “when the effects of A and G are controlled for”.

In other words, the technology (T) affects behavior (B) in the hypothesized way regardless of age (A) and gender (B). This conclusion would remain the same whether the path coefficients between A and/or G and B were significant, because the focus of the analysis is on B, the main dependent variable of the model.

Some special considerations and related analysis decisions usually have to be made in

more complex models, with multiple endogenous latent variables (i.e., variables to which arrows point), and also regarding the fit indices. For example, with multiple endogenous latent variables, you may want to add controls to all of them. Normally this will artificially reduce your APC (the average path coefficient, a model fit index); even though your ARS (the average R-squared, another model fit index) will most certainly go up.

Figure 2 shows a model created in Warp-PLS where the effect of “Proc” on “Effi” is analyzed, controlling for the effects of “ECU” and “ECUVar”. Control variables can be latent variables, as is the case here. “ECU” is a latent variable measured formatively through 16 indicators, as indicated by the “(F)16i” notation under the name of the variable.

Based on the results of the analysis we can say that “Proc” is significantly associated with “Effi”, regardless of “ECU” and “ECUVar”. Again, in this case it does not matter whether the effects associated with control variables are significant or not; in this case they are not. In models like the one above, with one main dependent variable, it is advisable to place the control variables on the right side of the model. This improves the readability of the model.

USING SECOND ORDER LATENT VARIABLES

Second order latent variables can be implemented in WarpPLS through two steps. These steps are referred to as Step 1 and Step 2 in the paragraphs below. Higher order latent variables can also be implemented, following a similar procedure, but with additional steps.

With second order latent variables, a set of latent variables scores are used as indicators of another latent variable. Often second order latent variables are decompositions of a formative latent variable into a few reflective latent variables, but this is not always the case. If this is the case, the scores of the component reflective latent variables are used as indicators of the original formative latent variables.

In Step 1, you will create a model that relates latent variables to their indicators, as in Figure 3(a). Only the latent variables and their indicators should be included. No links between latent variables should be created. This will allow you to calculate the latent variables scores for the latent variables, based on the indicators. You will then save the latent variables scores using the option “Save factor scores into a tab-delimited .txt file”, available from the “Save” option of the “View and save results” window menu, as shown in Figure 3(b).

In Step 2, you will create a new model where the saved latent variables scores are indicators of a new latent variable. This latent variable is usually called the second order latent variable, although sometimes the indicators (component latent variables) are referred to as second order latent variables. The rest of the data will be the same. Note that you will have to create and read the raw data used in the SEM analysis again, for this second step.

CHOOSING THE RIGHT WARPING ALGORITHM: THE ROLE OF THEORY

WarpPLS offers the following analysis algorithms: Warp3 PLS Regression, Warp2 PLS

Regression, PLS Regression, and Robust Path Analysis.

Many relationships in nature, including relationships involving behavioral variables, are nonlinear and follow a pattern known as U-curve (or inverted U-curve). In this pattern a variable affects another in a way that leads to a maximum or minimum value, where the effect is either maximized or minimized, respectively. This type of relationship is also referred to as a J-curve pattern; a term that is more commonly used in economics and the health sciences. Other nonlinear patterns that are noncyclical, such as logarithmic and exponential, can be easily modeled as sections of U (or J) curves.

The Warp2 PLS Regression algorithm tries to identify U-curve relationships between latent variables, and, if those relationships exist, the algorithm transforms (or “warps”) the scores of the predictor latent variables so as to better reflect the U-curve relationships in the estimated path coefficients in the model. The Warp3 PLS Regression algorithm, on the other hand, tries to identify a relationship defined by a function whose first derivative is a U-curve. This type of relationship follows a pattern that is more similar to an S-curve (or a somewhat distorted S-curve), and can be seen as a combination of two connected U-curves, one of which is inverted.

The PLS Regression algorithm does not perform any warping of relationships. It is essentially a standard PLS regression algorithm, whereby indicators’ weights, loadings and latent variable scores (a.k.a. factor scores) are calculated based on a least squares minimization sub-algorithm, after which path coefficients are estimated using a robust path analysis algorithm. A key criterion for the calculation of the weights, observed in virtually all PLS-based algorithms, is that the regression equation expressing the relationship between the indicators and the latent variable scores has an error term that equals zero. In other words, the latent variable scores are calculated as exact linear combinations of their indicators. PLS regression is the underlying weight calculation algorithm used in both Warp3 and Warp2 PLS Regression. The warping takes place during the estimation

Figure 3(a). Model relating latent variables to indicators

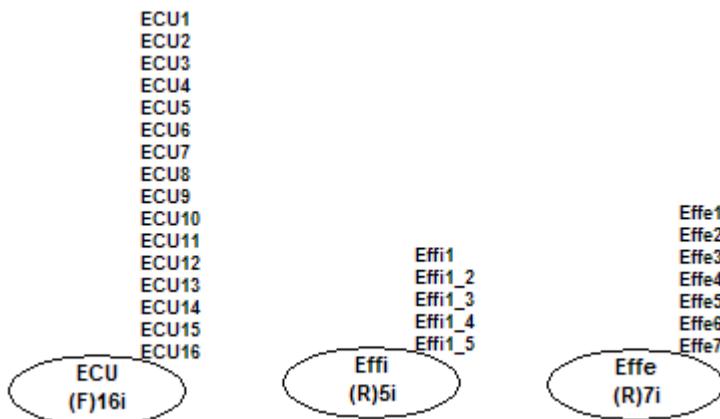
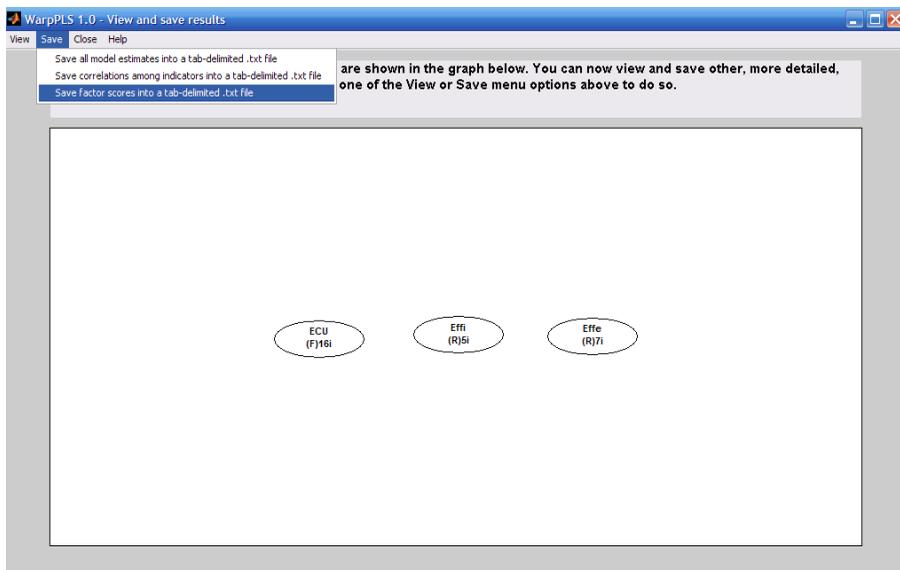


Figure 3(b). Saving latent variable scores



of path coefficients, and after the estimation of all weights and loadings in the model. The weights and loadings of a model with latent variables make up what is often referred to as the outer model, whereas the path coefficients among latent variables make up what is often called the inner model.

Finally, the Robust Path Analysis algorithm is a simplified algorithm in which latent variable scores are calculated by averaging all of

the indicators associated with a latent variable; that is, in this algorithm weights are not estimated through PLS regression. This algorithm is called “Robust” Path Analysis, because, as with most robust statistics methods, the P values are calculated through resampling. If all latent variables are measured with single indicators, the Robust Path Analysis and the PLS Regression algorithms will yield identical results.

So what algorithm should one use?

Generally it will be one of these: Warp3 PLS Regression, Warp2 PLS Regression, or PLS Regression. Only in a small number of instances, quite rare, will the Robust Path Analysis algorithm be the best choice. An example would be a “pure” path analysis, where all latent variables are measured through one single indicator; in this case, the variables will not be “latent” variables, strictly speaking.

If you analyze your dataset using different algorithms (e.g., Warp3 PLS Regression, Warp2 PLS Regression, and PLS Regression), usually the “best” algorithm will be the one leading to the most stable path coefficients. The most stable path coefficients are the ones with the lowest P values, whether the P values are obtained through bootstrapping or jackknifing. The best algorithm will also be the one leading to the highest average R-squared (ARS).

Another important consideration is theory. Does the theory underlying a hypothesized relationship between latent variables support the expectation of a U-curve or S-curve relationship? If the theory supports the expectation of a U-curve relationship, but not of an S-curve relationship, then you should favor Warp2 PLS Regression over Warp3 PLS Regression, even if the latter leads to the most stable path coefficients (i.e., with the lowest P values).

BOOTSTRAPPING OR JACKKNIFING? MAYBE BOTH

Arguably jackknifing does a better job than bootstrapping at addressing problems associated with the presence of outliers due to errors in data collection. Generally speaking, jackknifing tends to generate more stable resample path coefficients (and thus more reliable P values) with small sample sizes (lower than 100), and with samples containing outliers. With jackknifing, outlier data points do not appear more than once in the set of resamples, which accounts for the better performance (Chiquoine & Hjalmarsson, 2009).

Bootstrapping tends to generate more stable resample path coefficients (and thus more reli-

able P values) with larger samples, as well as with samples where the data points are evenly distributed on a scatter plot. Conversely, the use of bootstrapping with small sample sizes (lower than 100) has been discouraged (Nevitt & Hancock, 2001). This makes sense, as it is reasonable to expect an algorithm that performs quite well with large samples not to perform just as well with small samples, particularly when the algorithm features that make it perform well are sensitive to sample size variations.

Given that the warping algorithms are also somewhat sensitive to the presence of outliers, it is frequently a good idea to estimate P values with both bootstrapping and jackknifing. One can then use the P values associated with the most stable coefficients in research reports. There is no valid theoretical reason to assume that all P values must be generated with the same algorithm. An indication of resample set instability is a high P value (i.e., statistically insignificant) associated with path coefficients that could be reasonably expected to have low P values.

For instance, in an analysis of a dataset with a sample size of 100, a path coefficient of .2 or greater could be reasonably expected to yield a P value that would be statistically significant at the .05 level. If that is not the case, there may be a resample set stability problem. Another indication of instability in a resample set is a marked difference between the P values estimated through bootstrapping and jackknifing.

P values can be easily estimated using both resampling methods, bootstrapping and jackknifing, by following this simple procedure. First, run an SEM analysis of the desired model using one of the resampling methods, bootstrapping or jackknifing, and save the project. Then save the project again, this time with a different name. Next change the resampling method, and run the SEM analysis again, saving the second project again after the analysis is completed. Now each project file will have results that refer to one of the two resampling methods. The resulting P values can then be compared, even side-by-side if model estimates are saved in text files (which can be opened concurrently), and

the most stable ones used in a research report on the SEM analysis.

FIELD STUDIES AND SMALL SAMPLES

Let us assume that a researcher wants to evaluate the effectiveness of a new e-collaboration technology by conducting an intervention study in one single organization. In this example, the researcher facilitates the use of the new e-collaboration technology by 20 managers in the organization, and then measures their (i.e., the managers') degree of adoption of the technology and their effectiveness.

The above is an example of a field study. Often field studies will yield small datasets, which will not conform to parametric analysis (e.g., ANOVA and ordinary multiple regression) pre-conditions. For example, the data will not typically be normally distributed. WarpPLS can be very useful in the analysis of this type of data.

One reason is that, with small sample sizes, it may be difficult to identify linear relationships that are strong enough to be statistically significant (at P lower than 0.05, or less). Since WarpPLS implements nonlinear analysis algorithms, it can be very useful in the analysis of small samples.

Another reason is that P values are calculated through resampling, a nonparametric approach to statistical significance estimation. For small samples (i.e., lower than 100), jackknifing is the recommended resampling approach. Bootstrapping is recommended only for sample sizes greater than 100.

PROJECT FILES AND GEOGRAPHICALLY DISTRIBUTED RESEARCH COLLABORATION

A geographically distributed collaborative SEM analysis can be easily conducted using WarpPLS. Let us look at an example of an analysis that involved a few people in different states of the USA, as well as two people outside the country.

The collaborators were not only separated by large distances, but also operated in different time zones.

Yet, they had no problems collaborating. The collaboration was asynchronous – one person did some work one day, and shared it with the others, who reviewed the work in the next few days and responded.

Since all of the collaborators had WarpPLS installed on their computers, they exchanged different versions of a WarpPLS project file (extension “.prj”) with the same dataset. This way they were able to do analyses in turns, and discuss the results via email.

Each slightly different project file was saved with a different name – e.g., W3J_IO_2010_03_02.prj, W3B_IO_2010_03_02.prj, W2J_IO_2010_03_02.prj etc. In these examples above, the first three letters indicate the SEM algorithm used (W3 = Warp3 PLS Regression; W2 = Warp2 PLS Regression), and the resampling method used (J = jackknifing; B = bootstrapping). The second part of the name describes the dataset, and the final part the date. This is just one way of naming files. It worked for this particular project, but more elaborate file names can be used in more complex collaborative SEM analyses.

This geographically distributed collaborative SEM analysis highlights one of the advantages of WarpPLS over other SEM software: all that is needed for the analysis is contained in one single project file.

Moreover, the project file will typically be only a few hundred kilobytes in size. In spite of its small size, the file includes the original data, and all of the results of the analysis. The reason is that all of the SEM analysis results are stored in a format that allows for their rendering every time they are viewed. Plots of nonlinear relationships, for example, are not stored as large bitmaps, but as equations that allow WarpPLS to re-create those plots at the time of viewing.

COMBINING STANDARDIZED AND UNSTANDARDIZED RESULTS

SEM is essentially path analysis with latent variables (Kline, 1998; Maruyama, 1998; Muel-

ler, 1996). Path analysis is method developed by Sewall Wright (Wolfe, 1999; Wright, 1934, 1960), in which path models with multiple variables are analyzed, and where each variable is standardized.

To standardize a variable, one subtracts the variable mean from the values stored by the variable, and divides the resulting values by the variable's standard deviation. Once standardized, a variable becomes dimensionless. The values assumed by a standardized variable are expressed in standard deviations from the mean, where the mean and standard deviation are calculated based on the unstandardized version of the variable. For instance, a standardized value of -0.35 refers to a point on an axis (e.g., the horizontal axis, on a bidimensional graph) that is located -0.35 standard deviations from the mean.

The values stored by a standardized variable can then be compared with the values stored by a different standardized variable. This is impossible with variables measured on different units, if the variables are not standardized. For example, one cannot compare 10 kilograms with 15 dollars, but one can compare the corresponding standardized variables.

Given the above, the values reported by WarpPLS are standardized values. This is true for the values reported on models and on graphs. The path coefficients shown by WarpPLS on models, after an SEM analysis is completed, are standardized partial regression coefficients. Also, the plots provided by WarpPLS are based on standardized values.

The problem with standardized values is that they cannot be easily interpreted by practitioners, who are more interested in concrete unstandardized values than the more abstract corresponding standardized versions. So what can a researcher do, employing WarpPLS, to overcome this problem?

The solution is to use both standardized and unstandardized values and/or representations in reports. For example, a researcher may show one of the nonlinear plots generated by WarpPLS, where standardized values are shown along the axes; and also a chart created based

on the "Save grouped descriptive statistics into a tab-delimited .txt file" option (Kock, 2010a, pp. 3-5). These can be shown next to each other, as in Figures 4(a) and 4(b).

The second graph is much more meaningful to practitioners because it shows the actual number of electronic communication media used on the horizontal axis. Those refer to the number of electronic communication media with different features (e.g., e-mail, teleconferencing, telephone) used by each team. The vertical axis shows the perceived degree to which each team employed established project management techniques, measured on a Likert-type scale going from 0 to 10.

Note that when standardized values are used one can generate and display graphical representations including latent variables measured through multiple indicators (e.g., the latent variable "Proc", which is measured through 3 indicators). This is not possible with unstandardized values, because indicators are standardized prior to being used for the calculation of latent variable scores. Therefore, a chart with unstandardized values can only include single indicators of a latent variable (e.g., "Proc1").

The above leads to an implication, which is that standardized and unstandardized representations are likely to have the same general form when latent variables are measured using: (a) single indicators; or (b) a reflective measurement approach. That is, in these two situations, general association trends (curves or lines) should be the same for standardized and unstandardized representations.

When latent variables are measured using single indicators, standardized and unstandardized representations will have the same form because standardization is a process that does not change the shape of the association between two variables. The forms will be similar with reflective latent variables because in this case component indicators are expected to be highly correlated with latent variable scores.

However, with formative latent variables, standardized and unstandardized representations may differ significantly. In this case, it

Figure 4(a). Plot with standardized value

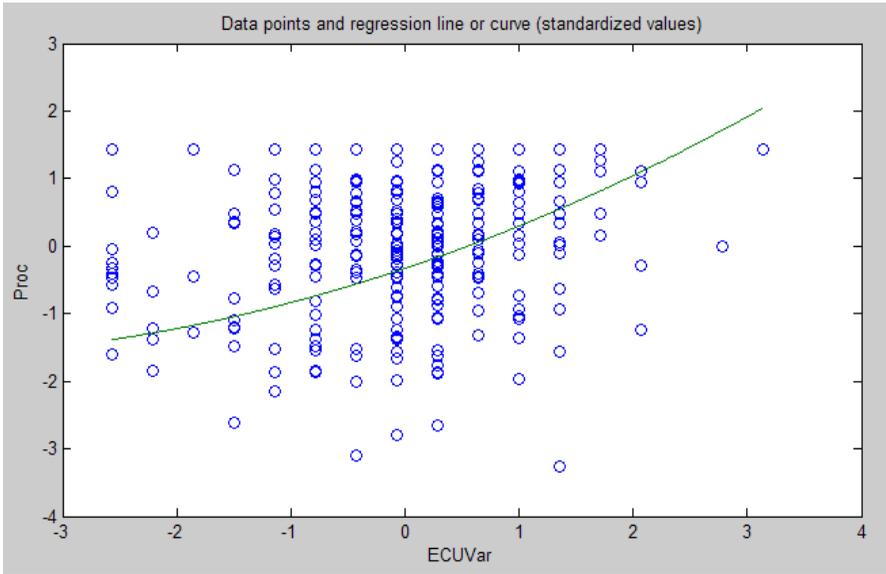
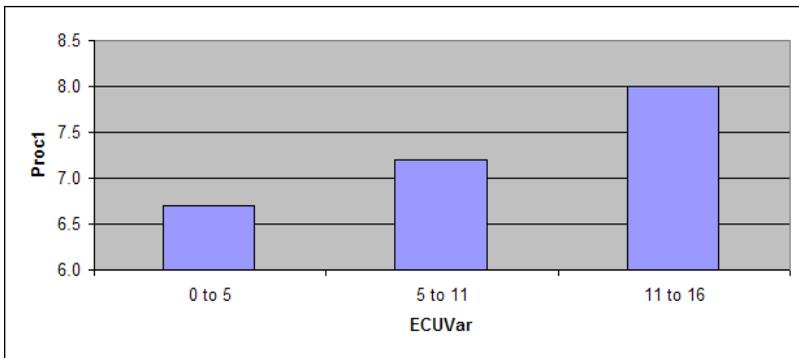


Figure 4(b). Chart with unstandardized values



would be more appropriate to show multiple unstandardized representations of a relationship between two latent variables (where at least one is formative) in research reports, one for each indicator, together with one standardized representation. This may clutter research reports and make them difficult to read though, because formative latent variables usually have significantly more indicators than reflective latent variables (Diamantopoulos, 1999; Diamantopoulos & Siguaw, 2006).

A NOTE OF CAUTION REGARDING THE USE OF FORMATIVE LATENT VARIABLES

The above discussion provides a solid basis for a warning: one should use formative latent variables with caution in SEM analyses using WarpPLS. It is not uncommon to see formative latent variables being created simply by casually aggregating indicators, without much concern about the indicators being actually facets of the

same construct (Diamantopoulos & Siguaw, 2002; Petter et al., 2007).

It is also important to stress that formative latent variables are better assessed when included as part of a model. This is preferable to analyzing formative latent variables individually; that is, as “models” that include one single latent variable. The loadings and cross-loadings table takes into consideration both formative and reflective latent variables in its calculation, and may suggest that some indicators do not “belong” to a formative latent variable.

For example, Table 1 shows the loadings and cross-loadings for three latent variables,

namely “ECU”, “Proc”, and “Effi”. The loadings and cross-loadings shown are from a pattern matrix, obtained after an oblique rotation of the loadings and cross-loadings from the structure matrix (Hair et al., 2009). The indicators are named starting with the name of the latent variable they refer to, followed by the numbers 1, 2, 3 and so on. One of the three latent variables is measured formatively, namely “ECU”, and its loadings are shown in shaded cells.

As it can be seen, the cross-loadings for the formative latent variable “ECU” are all low, which suggests that they do not actually “belong” to any other latent variable in the

Table 1. Indicator loadings and cross-loadings

	<i>ECU</i>	<i>Proc</i>	<i>Effi</i>
<i>ECU1</i>	0.587	-0.123	0.184
<i>ECU2</i>	0.591	0.001	0.074
<i>ECU3</i>	0.320	0.244	-0.217
<i>ECU4</i>	0.530	-0.022	0.015
<i>ECU5</i>	0.452	0.092	-0.172
<i>ECU6</i>	0.450	-0.045	0.033
<i>ECU7</i>	0.463	-0.155	0.011
<i>ECU8</i>	0.619	-0.092	0.090
<i>ECU9</i>	0.595	-0.062	0.026
<i>ECU10</i>	0.570	-0.101	-0.018
<i>ECU11</i>	0.402	0.119	-0.039
<i>ECU12</i>	0.459	0.154	-0.092
<i>ECU13</i>	0.469	0.074	-0.009
<i>ECU14</i>	0.422	0.026	-0.065
<i>ECU15</i>	0.395	0.100	-0.041
<i>ECU16</i>	0.475	-0.065	0.077
<i>Proc1</i>	-0.010	0.827	0.029
<i>Proc2</i>	0.002	0.896	-0.017
<i>Proc3</i>	0.008	0.821	-0.012
<i>Effi1</i>	0.001	-0.020	0.905
<i>Effi2</i>	0.001	-0.005	0.887
<i>Effi3</i>	-0.007	0.048	0.799
<i>Effi4</i>	-0.032	-0.085	0.852
<i>Effi5</i>	0.037	0.064	0.766

model. In this case, the model is somewhat simple, including only three latent variables. This check should be complemented with other checks, such as the P values associated with the weights for formative latent variables. The reason is that one cannot use standard tests of convergent validity and reliability with formative latent variables, because the indicators in formative latent variables are expected neither to be highly correlated with the latent variable scores nor with each other (Hair et al., 2009; Kock, 2010a).

Certain model parameters may sometimes become unstable due to collinearity. High collinearity among indicators is to be expected in reflective latent variable measurement, but not in formative latent variable measurement. In the context of formative latent variable assessment, collinearity may be reflected in unstable weights, where unexpected P values (usually statistically insignificant) are associated with weights.

In formative latent variables, indicators are expected to measure different facets of the latent variable, not the same “thing”. If two (or more) indicators are collinear in a formative latent variable, it may be a good idea to collapse them into one indicator. This can be done by defining second order latent variables, or creating a new indicator by averaging the collinear indicators. An alternative option is to simply eliminate all but one of the collinear indicators from the latent variable.

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