Chapter 11
Using WarpPLS in E-Collaboration Studies:
An Overview of Five Main Analysis Steps

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ABSTRACT

Most relationships between variables describing natural and behavioral phenomena are nonlinear, with U-curve and S-curve relationships being particularly common. Yet, structural equation modeling software tools do not estimate coefficients of association taking nonlinear relationships between latent variables into consideration. This can lead to misleading results, particularly in multivariate and complex phenomena like those related to e-collaboration. One notable exception is WarpPLS (available from: warppls.com), a new structural equation modeling software currently available in its first release. The discussion presented in this paper contributes to the literature on e-collaboration research methods by providing a description of the main features of WarpPLS in the context of an e-collaboration study. The focus of this discussion is on the software's features and their use and not on e-collaboration study itself. Particular emphasis is placed on the five steps through which a structural equation modeling analysis is conducted through WarpPLS.

INTRODUCTION

Multivariate analysis methods are particularly useful because they allow for the estimation of relationships among numeric variables controlling for the effects of multiple variables at the same time (Hair et al., 1987). Three commonly used multivariate analysis methods are multiple regression, path analysis, and structural equation modeling (SEM).

In multiple regression coefficients of association between one dependent variable and multiple independent or control variables are estimated all

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at once, as part of a multiple regression model. Those coefficients of association are standardized partial regression coefficients (Rencher, 1998), which are different from but analogous to Pearson correlation coefficients (Rosenthal & Rosnow, 1991).

In path analysis, coefficients of association in several multiple regression models that are connected to each other are estimated all at once. The coefficients of association are of the same type as those generated by multiple regression analysis, but in path analysis they are usually referred to as path coefficients.

Finally, in SEM, path analyses are conducted with various latent variables (LVs), which typically are perceptual variables that cannot be measured directly (e.g., perceived ease of use of an e-collaboration technology). In SEM each LV score is calculated as a weighted average of a set of variables, normally referred to as manifest variables or indicators, which are measured directly. Models can comprise a combination of multiple-indicator and single-indicator LVs in SEM.

While many conditions for convergence exist for the calculation of LV scores in SEM, and thus many approaches to SEM exist, the quantitative methods literature often classifies SEM approaches into two main types: covariance and variance-based (Gefen et al., 2000; Haenlein & Kaplan, 2004). The latter is also known as the PLS-based or component-based approach to SEM (Chin et al., 2003), where PLS usually stands for "partial least squares" (even though in the original version of the approach, it stood for "projection to latent structures"). PLS-based SEM has several key advantages over covariance-based SEM, including the following: (a) it appears to always yield a solution, even in complex models; (b) it does not require variables to meet parametric analysis criteria, such as multivariate normality and large sample sizes; and (c) it enables the estimation of parameters in models with formative LVs and moderating effects. One disadvantage of PLS-based SEM is that it typically does not yield fit indices, which are useful in the assessment of the overall fit between a model with multiple LVs and the dataset used in the SEM analysis.

Most relationships between variables describing natural and behavioral phenomena seem to be nonlinear, with U-curve and S-curve relationships being particularly common. Yet, typically neither PLS-based nor covariance-based SEM software estimate coefficients of association taking nonlinear relationships between LVs into consideration.

The only type of nonlinearity that is typically estimated by commercially available and open-source SEM software, which is of a different kind than the one just described, is that caused by the consideration of moderating effects. Moderating effects are often described as one of two main types of sources of nonlinearity in SEM analysis. The other type is the one associated with nonlinear relationships between LVs.

One notable exception to the above limitation is a SEM software called WarpPLS (Kock, 2010), currently available (from: warppls.com) in its first release, version 1.0. The discussion presented here contributes to the literature on e-collaboration research methods by providing a description of the main features of WarpPLS, in the context of an e-collaboration study. The focus of this discussion, however, is more on the use of the software than on the e-collaboration study itself. Particular emphasis is placed on the five main steps through a SEM analysis is conducted with WarpPLS

The E-Collaboration Study

Several screens are shown here summarizing analysis results based on data from an e-collaboration study. The study involved 290 teams tasked with developing new products, goods or services, in a variety of organizations. Data related to five LVs were collected as part of this study. The LVs are indicated here as "ECU", "ECUVar", "Proc", "Effi", and "Effe".

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