To PLS or Not to PLS: That is the Question

Panel

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ABSTRACT

PLS is used quite widely in the MIS field, but some evidence questioning its efficacy is mounting, at least in the eyes of the "nays". In this panel we bring together advocates of multiple perspectives of the debate, to lay the evidence on the table and to vigorously explore the various points of view.

Keywords

PLS, CB-SEM, Sample Size, Non-Normal Data, Measurement Error, Capitalization On Chance, Consistency, Consistency-at-Large.

INTRODUCTION

Lately there has been some controversy around PLS's supposed strengths and whether it is the powerful technique we thought it was. At this point in time it would be beneficial for the MIS community members to have several sides of the debate explained to them at the same time, and to have reasonable people explore the arguments on both sides, rather than each side talking only to itself**.**

ISSUES THAT HAVE BEEN RAISED

The Advantage at Small Sample Size or With Non-Normal Nata. On the CON side, Goodhue, Lewis and Thompson (2012), and Rönkkö and Evermann (forthcoming) have presented evidence challenging these supposed advantages. Gefen, Rigdon and Straub (2011) have suggested that this is no longer a reason to choose PLS over CB-SEM, and Goodhue, Lewis and Thompson (2012) have shown evidence that PLS, regression and CB-SEM are all remarkably robust to moderate departures from normality, and equally so.

However, on the PRO side, PLS can estimate models with more variables or parameters than observations, and can estimate models with interactions and other nonlinear effects of reflective and formative constructs (Henseler & Chin, 2010; Henseler, Fassott, Dijkstra & Wilson, 2012). UTAUT (Venkatesh, Morris, Davis & Davis 2003) and other complex models of IS research have benefitted from this characteristic of PLS. In contrast to other methods (e.g., CB-SEM), neither the convergence behavior nor the Type-I error of PLS estimates is affected by non-normal data.

Advantages from minimizing the effect of measurement error. On the CON side, Rönkkö and Ylitalo (2010) and Rönkkö and Evermann (forthcoming) used Monte Carlo simulation to test the effect of measurement error, and found that while the indicator weightings in PLS maximized explained variance in the data, they also resulted in biased estimates and did not control for measurement error.

On the PRO side, in comparison to single-indicator measurement, PLS in combination with multi-indicator measurement reduces the effect of measurement error. It excels over regression with summed scores if indicators vary in reliability and if the latent variables are embedded in a nomological net.

Evidence of capitalization on chance and its impact on PLS's value in prediction. On the CON side, Goodhue, Lewis and Thompson (2013) presented a paper on this issue at HICSS, concluding that PLS does capitalize on chance under circumstances that are not unusual in MIS research.

On the PRO side, capitalization on chance is indeed an issue, but is mainly limited to very small models with weakly related constructs. It is pivotal to understand under which conditions this phenomenon occurs.

OVERALL PERSPECTIVES

On the CON side, PLS was accepted by the MIS research community on the basis of many claimed advantages that have not been born out on closer inspection. It has some true deficits in certain conditions occurring in MIS research. There are other techniques, perhaps not quite so convenient to use, that do not have these deficits.

On the PRO side, PLS has helped MIS research advance in several ways, and it keeps on being a powerful and useful technique for explorative and predictive research (Gefen, Ridgon, & Straub, 2011; Hair, Ringle, & Sarstedt, 2011; Marcoulides, Chin, & Saunders, 2009; Ringle, Sarstedt, & Straub, 2012). Not only has the use of PLS made researchers sensitive for the quality of measurement (it has become standard to assess convergence and discriminant validity, see Ringle, Sarstedt, & Straub, 2012), it has also allowed to analyze indirect and total effects of explanatory variables (Albers 2010), and to combine reflective and formative measurement in one PLS path model. Further, the development of PLS has gained momentum. Researchers mainly follow two directions to further develop PLS: Some propose to focus on the predictive capabilities of PLS and to develop tailor-made assessment criteria (e.g., Rigdon, 2012). Others (e.g. Dijkstra & Henseler, 2013; Goodhue et al., 2012) suggest correcting PLS path coefficients for attenuation.

ORGANIZATION OF THE PANEL

Each panel member will present some of the evidence that he finds persuasive, and will give his resulting perspective on PLS. There will be plenty of time for discussion between panel members and with the audience.

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