Accepted Manuscript

|  |
| --- |
| **Comments on Evermann and Rönkkö: Recent Developments in PLS** |
| |  |  | | --- | --- | | **Dale Goodhue**  Professor Emeritus  Terry College of Business  University of Georgia  *dgoodhue@uga.edu* | | | **Will Lewis**  Assistant Professor  College of Applied Science and Technology  Illinois State University  *wlewis2@ilstu.edu* | **Ron Thompson**  Professor Emeritus  School of Business  Wake Forest University  *thompsrl@wfu.edu* | |
|  |

Please cite this article as: Goodhue, Dale; Lewis, Will; Thompson, Ron: Comments on Evermann and Rönkkö: Recent Developments in PLS, *Communications of the Association for Information Systems* (forthcoming), In Press*.*

This is a PDF file of an unedited manuscript that has been accepted for publication in the *Communications of the Association for Information Systems*. We are providing this early version of the manuscript to allow for expedited dissemination to interested readers. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered, which could affect the content. All legal disclaimers that apply to the *Communications of the Association for Information Systems* pertain. For a definitive version of this work, please check for its appearance online at <http://aisel.aisnet.org/cais/>.

Comments on Evermann and Rönkkö: Recent Developments in PLS

|  |  |
| --- | --- |
| **Dale Goodhue**  Professor Emeritus  Terry College of Business  University of Georgia  *dgoodhue@uga.edu* | |
| **Will Lewis**  Assistant Professor  College of Applied Science and Technology  Illinois State University  *wlewis2@ilstu.edu* | **Ron Thompson**  Professor Emeritus  School of Business  Wake Forest University  *thompsrl@wfu.edu* |

|  |
| --- |
| Abstract: |
| Evermann and Rönkkö (2022) have provided an excellent overview of recent findings relating to the use of Partial Least Squares (PLS). Their overall message is that *if* researchers decide to use PLS, they need to ensure that they follow best practices to reduce the possibility of obtaining misleading or erroneous results. We generally agree with their assessment, but go further to recommend against the use of PLS. We demonstrate exactly how PLS introduces biases, arguing that the algorithm violates accepted norms for statistical inference. Our final recommendation is for the Editors-in-Chief of top IS research journals to convene a task force to assess the advisability of continuing to accept articles where PLS is used for publication in IS journals. |
| **Keywords:** Partial least squares, PLS, Biased estimates |

[Department statements, if appropriate, will be added by the editors. Teaching cases and panel reports will have a statement, which is also added by the editors.]

[Note: this page has no footnotes.]

This manuscript underwent [editorial/peer] review. It was received xx/xx/20xx and was with the authors for XX months for XX revisions. [firstname lastname] served as Associate Editor.] **or** The Associate Editor chose to remain anonymous.]

# Introduction

We greatly appreciate the opportunity to provide comments on the paper authored by Evermann and Rönkkö (2022). Overall, we are very supportive of their positions concerning the use of partial least squares (PLS) within the information systems (IS) research community (and in the larger research community). Rather than repeating many of the points they raise, we provide some additional insights in support of their positions, and also provide an additional recommendation relating to the use of PLS going forward.

Here is a brief summary of the points we wish to emphasize or present, with details following.

* The only difference between PLS and regression using summed scale scores is how the PLS algorithm weights construct indicators to create construct scores. Proponents of PLS argue that this differential weighting is superior to summed scales. Critics of PLS argue that it capitalizes on chance, leading to biased path estimates.
* The PLS algorithm is complex. This makes it difficult for researchers to understand exactly how it works. Here we use a step-by-step examination of the PLS algorithm to demonstrate its flaw. More specifically, we show when and how it capitalizes on chance correlations leading to biased and potentially spurious results.
* Given the early and sustained controversy about PLS, its rapid adoption within the IS research community is perhaps surprising. We provide insights on how we believe that adoption and propagation took place.
* On-going criticism of PLS, and efforts to counter those, have resulted in many improvements to the original PLS software. None of these enhancements, however, address the underlying flaw in the PLS algorithm.
* The lively debate over the past decade or so between critics and proponents of PLS has not resulted in any reduction in the use of PLS (at least within the IS research community). Realistically, additional criticisms will also probably not result in any change in behavior. To address this situation, we propose that the Editors-in-Chief of top IS journals collaborate on creating an independent PLS task force to provide unbiased recommendations on the future use (or non-use) of PLS within the IS research community.

## The PLS Algorithm

Evermann and Rönkkö (2021) provide a general explanation of how the PLS algorithm works (section 2.2, Principles of PLS). A more detailed explanation based on Barclay, Higgins & Thompson (1995, page 292) is provided below. Throughout this comment we use labels on constructs and paths that are comparable to the labels in Evermann & Rönkkö’s Figure 1.

Here is the description from Barclay et al. (1995).

1. In the first PLS iteration, an initial value for  is formed by simply summing the values x4 …, x6 (i.e. the weights 4 . . . 6 are set to 1).
2. To estimate the weights from x1, x2, and x3 to  [1 . . ., 3], first a regression is done with  as the dependent variable and x1 – x3 as the independent variables, resulting in 1, 2, and 3.
3. These estimates are then used as weights [1 . . ., 3] in a linear combination of x1 – x3  giving an initial value for 
4. The loadings4-6 are then estimated by a series of simple regressions ofx4 . . ., x6 on 
5. The next step uses the estimated loadings, transformed into weights, to form a linear combination of x4 – x6  as a new estimate of 

This procedure (steps 2 through 5) continues to iterate until the difference between consecutive iterations is extremely small, reaching the stop criterion selected by the user.

## How PLS Capitalizes On Chance

The problem for IS researchers with the PLS algorithm is that many of those researchers (like us!) have not taken the time to analyze the algorithm in detail in order to understand what, in fact, PLS is doing. Rönkkö (2014) explored the issue of how PLS capitalizes on chance correlations in the indicator data in great detail, both mathematically and through simulations. We take a perhaps simpler and more direct approach here, showing step-by-step how the algorithm works**.** Our contribution is to add detail to Barclay, Higgins & Thompson’s description, using our Figures 2a, 2b, 2c, and 2d. Our detailed example is focused on the PLS Mode A algorithm.

Assume that the starting position is as shown in Figure 2a. This figure is adapted from Barclay et al. (1995), and Evermann and Rönkkö’s (2021) Figure 1.

|  |
| --- |
|  |
| Figure 2a (PLS Starting Position) |

**Step 1:** In Step 1 of the PLS procedure (shown in Figure 2b below), an initial value for  is formed by simply summing the values x4 …, x6 (i.e. the weights 4 . . . 6 are set to 1). In other words, the x4 through x6 indicators are weighted equally.

|  |
| --- |
|  |
| Figure 2b (PLS Step 1) |

**Step 2 (Figure 2c below):** To estimate the weights from x1, x2, and x3 to  [1 . . ., 3], first a regression is done with  as the dependent variable and x1 – x3 as the independent variables, resulting in (regression estimates) 1, 2, and 3. This regression configuration seems a bit strange, given that we can see from Figure 2a that *x1 , x2, andx3 are indicators of  not *, and have no direct relationship to ****

|  |
| --- |
|  |
| Figure 2c (PLS Step 2) |

We submit that the only thing gained from Step 2 is that the PLS algorithm now knows the degree to which each of the x1 through x3 indicators are correlated to . This knowledge is used in Step 3.

**Step 3 (Figure 2d Below)**: These estimates (the regression loadings produced in Step 2 (andi.e., essentially the correlations[[1]](#footnote-1) between x1, x2 and x3 with ) are then used as weights [1 . . ., 3] in a linear combination of x1 – x3  giving an initial value for In other words, *the x1 through x3 indicator that is most correlated with  will be given the most influence in producing a value for . The one least correlatd with  will have the least influence, etc.*

This is obviously a very different approach than giving equal weights to each indicator. It will bias the value of  toward. Thus after steps 2 and 3, is guaranteed to be biased toward .

|  |
| --- |
|  |
| Figure 2d (PLS Step 3) |

1. **Step 4** (not shown in a figure):The loadings4-6 are then estimated by a series of simple regressions ofx4 . . ., x6 on 
2. **Step 5** (not shown in a figure): The next step uses the estimated loadings, transformed into weights, to form a linear combination of x4 – x6  as a new estimate of 

Similar to the situation with steps 2 and 3, with steps 4 and 5 becomes biased toward  through the use of another questionable regression configuration.

This procedure (steps 2 – 5) iterates until the difference between consecutive iterations is extremely small, reaching the stop criterion selected by the user.

As the iterations through the PLS process continue, the indicator values remain constant (they are never changed), but the estimates of  and  are increasingly biased toward each other, though by smaller and smaller additions. When the changes to  and  get below the cutoff point, the iteration stops and the values for  and are fixed and used in the next phase of PLS: regression equations estimating the value of β.

Through this process, PLS will have capitalized on chance correlations in the data to bias the value of  to something higher than its true value. Rönkkö (2014) showed that PLS capitalizes on chance by taking advantage of chance correlations between random error included in the X1-X3 and X4-X6 indicators. Above we have given a more visual accounting of how this capitalization on chance occurs.

## Opposing Views of Differential Weighting by PLS

The question of whether differential weighting of indicators by PLS is beneficial or not is the crux of the ongoing debate about the use of PLS. Critics argue that the differential weighting is based on chance correlations in the data that can lead to biased and possibly spurious results.

Proponents argue that the differential weighting of indicators for constructs results in better estimates than using regression with equal weighting. For example, Chin, Marcolin & Newsted (2003) asserted:

“In summing items into a single measure, the assumption is made that all items are equally reliable. However, this summing approach, while reducing measurement error, is suboptimal relative to the PLS algorithm. PLS treats each indicator separately, allowing each item to differ in the amount of influence on the construct estimate. Therefore, indicators with weaker relationships to related indicators and the latent construct are given lower weightings**...** resulting in higher reliability for the construct estimate and thus stronger theoretical development”. (Chin, et al., 2003, p.194, emphasis added).

We need to ask which “latent construct” in the text above Chin et al. (2003) are referring to. Clearly, in Step 2 of the PLS algorithm, and as shown in Figure 2(b) and 2(d), it is not the construct that the indicators are supposed to be associated with (), but instead the construct on the other side of the hypothesized link (). The weaker the relationship to the lower the weighting. The stronger the relationship to the higher the weighting. The new value for  is therefore clearly biasedtoward 

We recognize that there could be an argument for why, in Step 3 of the PLS algorithm, one might want to give more weight to the x1 - x3 values that are most correlated with The argument involves leaning on the *assumption* that the real correlation between  and  (that is, β) is non-zero *as hypothesized*. Given that assumption, the x1 - x3 indicator that most strongly supports that hypothesis might be assumed to be the most reliable of the three x1 - x3 indicators. This assertion is perhaps why Chin et al. (2003, pg. 190) argued that PLS increases the weights of those indicators that are more “predictive” and “reliable”.

But one cannot use the *assumption* that a hypothesized relationship is true as part of the proof that there is a true relationship (as this could lead to false positives). By weighting the indicators differentially based on how much support they provide for the hypothesis, PLS is biasing the test of the hypothesis. It would be equally inadmissible to give the highest weights to the indicators that tend to disprove the hypothesis (as this could lead to false negatives).

## How Did We (the IS Research Community) Get Here?

Early use of PLS within the IS research community began in the late 1980’s (e.g., Rivard & Huff, 1988). Articles explicitly supporting the use of PLS in IS appeared during the 1990’s (e.g., Barclay et al., 1995[[2]](#footnote-2); Chin, 1998). These articles provided claims relating to the supposed superiority of PLS over alternative techniques, including its supposed efficacy for early-stage research, small sample size, and non-normal data. Many researchers who adopted PLS cited these articles to justify its use. The development of easy-to-use software also contributed to its popularity.

Early adopters of PLS most likely believed that they were at the forefront of employing a technique that was superior to “first generation” techniques (e.g., factor analysis, regression with summed scores). PLS offered perceived advantages such as converging with models and data samples where covariance-based structural equation modeling (CB-SEM) techniques would not. One reason that researchers used PLS was because it produced results that were more likely to be viewed positively by reviewers during the journal review process, both because it allowed researchers to show they were using the “latest” innovations in statistical analysis, and perhaps because PLS tended to produce apparently stronger results for hypothesis testing.

## Recent Developments in PLS Do Not Address the Flaw

Evermann & Rönkkö (2021) provide an excellent overview of recent developments in PLS, many of which were initiated in response to criticisms of the technique. We agree with Evermann & Rönkkö (2021) that while these individual enhancements have helped address some of the limitations with the PLS program, *none of them address the underlying flaw in the PLS algorithm.* As they put it, “...PLS looks increasingly like a hodgepodge of kludges added upon kludges” (Evermann & Rönkkö, 2021). We also agree with them that it is inappropriate for researchers to cite old, outdated reference articles (e.g., Barclay et al., 1995; Chin, 1998) to justify a decision to use PLS. These justifications often ignore more recent and more definitive criticisms of the algorithm.

## Alternatives to PLS

Evermann & Rönkkö (2021, Section 5) have done a very good job of identifying alternatives to PLS, including CB-SEM, generalized structure component analysis (GSCA), and regression with summed scales. We note that one of the attractions for some PLS users might be the existence of easy-to-use software that can handle complex models. If that is in fact a contributing factor, we recommend that those interested in the use of regression consider the PROCESS macro created by Hayes (2018), which is very popular within the management (organizational behavior) academic discipline.

## How Big of a Deal is This?

When one follows the PLS algorithm step by step as we have done here, it is as if “the veil has been lifted.” We have shown how the PLS algorithm (in steps 2 and 3, as well as in steps 4 and 5) capitalizes on chance correlations in the indicators to give the highest weights to indicators that most support the hypothesis and the lowest weights to indicators that do not support the hypothesis. Consistent with this, Rönkkö (2014) has shown that when there are correlated errors across the independent and the dependent constructs in a regression, PLS’s algorithm capitalizes on that correlated error to bias path estimates.

Goodhue et al.’s (2012, pg. 997) findings are consistent with those of Rönkkö (2014). Across a range of sample sizes and effect sizes, LISREL had no path estimate bias, while both PLS and regression had negative biases. When PLS and regression results were corrected for reliability, regression results fell into line with the LISREL findings (zero % bias), but PLS had a *positive* bias of 10% to 15% when the effect size of the link between constructs was small. This positive bias (overestimation) may be because smaller effect size means weaker paths and a corresponding increase in measurement error in the path estimates. Since PLS’ capitalization on chance depends on random error in the indicators, smaller effect size gives PLS more opportunity to capitalize on chance.

PLS’ selective weighting of the indicators cannot be justified unless one assumes that the hypothesized relationships are true. Beginning a statistical inference process by assuming the hypothesis is true is not consistent with accepted practice. As a result, the evidence is very strong that the PLS algorithm is flawed.

We have focused here on the use of PLS with common factor models. While some commentators have recommended only using PLS with composite models, as Evermann & Rönkkö (2021) note, PLS has been (and continues to be) employed with common factor models. As long as that is the case, the biases introduced by PLS that we have described will be present.

Now that the veil over PLS (i.e., its inscrutability) has been removed, authors who use the technique need to acknowledge to themselves that they conducted their analysis under the assumption that the hypothesized relationship was true, and they need to be transparent with readers and reviewers of their papers that they have departed from the usual standards in hypothesis testing for statistical inference.

This is actually a pretty big deal.

# Recommendations and Conclusion

Taking a step back, we believe that there are basically four options with respect to the future use of PLS within the IS research community.

1. **Option 1**: stop the use of PLS, and employ alternatives such as CB-SEM or regression with summed scales. This option would remove the possibility of obtaining spurious results through use of the PLS algorithm. Instead, researchers would be required (through the review process) to use readily available alternatives.
2. **Option 2**: use summed scale scores with PLS. This would remove the possibility of obtaining spurious results through the use of the PLS algorithm and thus be tantamount to Option 1, as it would result in obtaining exactly the same results as would be obtained with regression. But it would also perhaps allow PLS software rights owners the ability to salvage some of their investment by allowing continued use of their user-friendly front ends and other useful advancements (consistent estimations, bootstrapping, etc.) along with a regression algorithm.
3. **Option 3**: if PLS is to be used, require that minimum standards (those recommended by Evermann & Rönkkö, 2021) be enforced via the review process. This will reduce (but not eliminate) the possibility of obtaining spurious results through the use of the PLS algorithm.
4. **Option 4**: retain the status quo. Allow IS researchers to employ PLS for their analyses, without requiring agreed upon minimum standards for its use. The possibility of obtaining spurious results from the use of the PLS algorithm will continue unabated. Damage to the reputation of the IS research community in general, and more specifically to the reputation of the IS journals that publish papers where PLS is employed, will continue.

Evermann & Rönkkö (2021) have advocated for Option 3. We are advocating for Options 1 or 2.

## One additional recommendation beyond those of Evermann and Rönkkö

As we noted above, repeated criticisms on the use of PLS within the IS research community has not altered researchers’ behavior. Realistically, we do not expect this situation to change any time soon, without some type of external impetus. For that reason, we recommend that the Editors-in-Chief of major IS journals collaborate to create a PLS Task Force to examine the available evidence and to provide unbiased recommendations concerning the future use of PLS within the IS research community. This Task Force should be comprised of expert statisticians from outside the IS community who have no potential conflicts of interest (either real or perceived) relating to this issue.

In conclusion, we sincerely appreciate the insights and recommendations offered by Evermann & Rönkkö (2021), and we hope that our comments provide a positive contribution to the conversation that they have renewed.

# References

Barclay, D., Higgins, C. & Thompson, R. (1995). The partial least squares approach to causal modeling: personal computer adoption and use as an illustration. *Technology Studies: Special Issue on Research Methodology*, 2(2), 285-324.

Chin, W.W. (1998). The partial least squares approach to structural equation modeling. In G. Marcoulides (Ed.), *Modern Methods for Business Research*, (pp. 295-336). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Chin, W.W., Marcolin, B., & Newsted, P. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: results from a monte carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research,* 14(2), 189-217.

Davis, F., Goodhue, D. & Thompson, R. (1990). A comparison of PLS with regression and LISREL. Presented at the *International Conference on Information Systems*, Copenhagen, December.

Evermann, J. & Rönkkö, M. (2021). Recent developments in PLS. *Communications of the AIS*, forthcoming.

Goodhue, D., Lewis, W. & Thompson, R. (2007). Research note - statistical power in analyzing interaction effects: questioning the advantage of PLS with product indicators. *Information Systems Research*, 18(2), 211-227.

Goodhue, D., Lewis, W. & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS Quarterly*, 36(3), pp. 981-1001.

Hayes, A. F. (2018). *Introduction to Mediation, Moderation and Conditional Process Analysis: A Regression-Based Approach*, New York, NY: The Guilford Press.

Rivard, S. & Huff, S. (1988). Factors of success for end-user computing. *Communications of the ACM*, 31(5), 552-561.

Rönkkö, M. (2014). The effects of chance correlations on partial least squares path modeling. *Organizational Research Methods*, 17(2), 164-81.

Rönkkö, M. & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods*, 16(3), 425-448.

# About the Authors

**Dr. Dale L. Goodhue** is professor emeritus in the MIS department in the Terry College of Business at the University of Georgia. His research interests have included measuring the impact of task-technology fit on performance, and the costs and benefits of data integration and other IS infrastructures/resources such as Data Warehousing and ERP systems. His work is published in *Decision Sciences*, Information Systems Research, *Management Science*, *MIS Quarterly*, *Sloan Management Review*, and other journals.

**Will Lewis** is an Assistant Professor of Information Systems in the School of Information Technology at Illinois State University. His research interests include technology adoption, research methods, and computer-based testing.

**Ron Thompson** is Professor Emeritus in the School of Business at Wake Forest University. He holds a Ph.D. from Western University (London, Canada) and is a former Senior Editor at MIS Quarterly. His work has been published in a variety of academic journals, including *MIS Quarterly*, *Information Systems Research*, and the *Journal of MIS*. His research interests include technology adoption and research methodology.

Copyright © 2022 by the Association for Information Systems. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and full citation on the first page. Copyright for components of this work owned by others than the Association for Information Systems must be honored. Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers, or to redistribute to lists requires prior specific permission and/or fee. Request permission to publish from: AIS Administrative Office, P.O. Box 2712 Atlanta, GA, 30301-2712 Attn: Reprints are via e-mail from publications@aisnet.org.

1. The three regression loadings are literally the correlations between the three x1, x2 and x3 indicators and , divided by the covariance matrix of the 3  x variables.  = (x’x)-1(x’y) [↑](#footnote-ref-1)
2. One of the co-authors of these comments (Thompson) was an early proponent of the use of PLS. A second co-author (Goodhue) was an early skeptic of PLS (Davis, Goodhue & Thompson, 1990). As more research emerged that de-bunked many of the claims relating to PLS (e.g., Goodhue, Lewis & Thompson, 2007, 2012; Rönkkö & Evermann 2013; Rönkkö, 2014), Thompson changed his position and now advocates against the use of PLS. [↑](#footnote-ref-2)