Segmentation of PLS-Path Models by Iterative Reweighted Regressions

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Abstract

Uncovering unobserved heterogeneity is a requirement to obtain valid results when using the structural equation modeling (SEM) method with empirical data. Conventional segmentation methods usually fail in SEM since they account for the observations but not the latent variables and their relationships in the structural model. This research introduces a new segmentation approach to variance-based SEM. The iterative reweighted regressions segmentation method for PLS (PLS-IRRS) effectively identifies segments in data sets. In comparison with existing alternatives, PLS-IRRS is multiple times faster while delivering the same quality of results. We believe that PLS-IRRS has the potential to become one of the primary choices to address the critical issue of unobserved heterogeneity in PLS-SEM.

Keywords: *Clustering, genetic algorithm, partial least squares, path modeling, PLS-IRRS, PLS-SEM, reweighted regressions, segmentation, structural equations modeling*

1. Introduction

Uncovering unobserved heterogeneity is a critical issue in covariance-based and variance-based structural equation modeling (SEM) to ensure validity of results (Becker, Rai, Ringle, & Völckner, 2013; Jedidi, Jagpal, & DeSarbo, 1997). In variance-based SEM, with latent variables using partial least squares path modeling (PLS; Hair, Hult, Ringle, & Sarstedt, 2014; Lohmöller, 1989; Wold, 1982), the structural model is given by

$$\eta = B\eta + \zeta \, ; \tag{1}$$

η represents the column vector of latent variables, B the matrix of path coefficients between latent variables, and ζ symbolize the column vector of structural regression models' errors. The model is recursive (i.e., no circular relationships in the structural model). Hence, B is a lower trigonal matrix with zeroes on the diagonal. The measurement models of the latent variables are defined as,

$$x = \Lambda\eta + \varepsilon \, , \tag{2}$$

whereby x represents the vector of manifest variables in the measurement models, Λ is the matrix of regression coefficients in the latent variables' measurement models, η, again, is the column vector of latent variables, and ε symbolizes the column vector of errors in the measurement models of the latent variables.

Researcher can account for observed heterogeneity by accordingly grouping the data a-priori and by running PLS multigroup analyses (PLS-MGA) (Hair et al., 2014; Sarstedt, Henseler, & Ringle, 2011). If theory does not support adequate knowledge on observed heterogeneity, researchers should check their results for unobserved heterogeneity to ensure the validity of their findings. They can generalize their findings from the sample drawn to the underlying population of their research when heterogeneity is not an issue. Otherwise, the results of the aggregate data set may be invalid and unreliable entailing misleading findings and false conclusions (Becker et al., 2013; Jedidi et al., 1997). Hence, researchers must account for the unobserved heterogeneity by forming adequate groups of observations.

The development of appropriate methods to uncover unobserved heterogeneity in variance-based SEM using PLS is critical to ensure validity and reliability of results (Becker et al., 2013; Hair, Sarstedt, Ringle, & Mena, 2012). For this reason, researchers developed PLS segmentation approaches (for an overview, see Sarstedt, 2008). This research contributes to existing research by developing the iterative reweighted regressions segmentation method for PLS (PLS-IRRS), which is superior to other previously introduced PLS segmentation methods. Without a performance loss regarding the quality of the segmentation solution, PLS-IRRS is a particularly fast method, which is generally applicable to all kinds of PLS path models. Thereby, we establish PLS-IRRS as a new standard means of assessing results in research projects and practical applications of the PLS path modeling method.

2. Method

Finding the best segmentation solution for a goal criterion is a combinatorial data assignment problem. The complexity of the problem increases exponentially with higher numbers of observations and/or higher numbers of segments (Cowgill, Harvey, & Watson, 1999). Conventional segmentation methods usually fail in SEM since they account for the observations but not the latent variables and their relationships in the structural model. Ringle, Sarstedt, and Schlittgen (2014) propose a genetic optimization algorithm to address effectively the segmentation problem in PLS. The advantage of genetic algorithms lies in the fact that they have a high probability not to stay in a local minimum but investigate many constellations, which are at least near to as many local optima as possible. The assignment problem's target function thereby improves in a non-smooth manner. The heuristic solution of the genetic algorithm follows a deterministic improvement, if possible. Even though the PLS-GAS method provides very good solutions, it is computationally demanding and needs a relatively long time to arrive at the final solution. Thus, the basic idea of an improved method is to obtain segmentation solutions of the same or possibly better quality by using a considerably smaller number of computations, which translates into a significantly lower time needed.

The new PLS-IRRS approach builds on an idea introduced by Schlittgen (2011) for clusterwise robust regression. In robust regression, M-estimators down-weight observations with extreme values of the dependent variable. Thereby, they mitigate the influence of outliers in the data set. One method to compute M-estimators is iteratively reweighted least squares. The weights are determined by the residuals and the larger the residuals, the smaller the weights. Since PLS is basically a system of least squares regressions to estimate the parameters, it is possible to use the idea of robust regression for determining a group of data and to address the segmentation problem. To adapt this idea for PLS segmentation, outliers are not treated as such but as their own segment. Hence, when robust regression identifies a group of similar outliers, they may become a data group of their own and represent a segment-specific PLS solution. On the other hand, within a group of data, a M-estimator down-weights inhomogeneous observations when returning the segment-specific PLS solution.

We start with a random choice of weights w_{ik}, where $\sum_{k=1}^{g} w_{ik} = 1$ for all $i = 1,..n$, whereby i indicates an observation and k=1,…,g the different groups. For the g group vectors $(w_{1k},...,w_{nk})'$ we determine the path model via the PLS algorithm (Lohmöller, 1989; Wold, 1982) and weighted regressions. The structural model residuals of all regressions determine the assignment of observations to the different groups. Observation i is assigned to the data group where the sum of its squared residuals is smallest. Then the inverses of these sums are scaled to sum to 1 for all i observations to obtain new weights. The procedure is then repeated with the new weights and the iteration stops when the estimates stabilize. The use of iteratively reweighted regressions is the reason for calling this novel PLS segmentation method PLS-IRRS; Figure 1 presents the PLS-IRRS algorithm.

A key element of PLS-IRRS is the computation of R_w^2, which requires some additional explications. Every regression equation in structural model builds on all observations at once. One of these equations with g clusters can be written as

$$y = \mathrm{X}\beta + \sum^{1/2} \varepsilon \quad . \qquad (3)$$

Following a suitable ordering of the observations

$$X = \begin{pmatrix} X_1 & 0 & \dots & 0 \\ 0 & X_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \dots & \dots & X_g \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_g \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_g \end{pmatrix} \sim (0, \mathrm{I}), \qquad (4)$$

$\Sigma^{1/2}$ is a diagonal matrix with the standard deviations of the errors of the k th cluster on the rows corresponding to block k. The weighting of the regressions uses the diagonal matrix

$\mathrm{W} = \mathrm{diag}(\Sigma)^{-1}$. A weighted regression's determination coefficient R_w^2 is given by:

$$R_W^2 = \frac{SS_{W0} - SS_W}{SS_{W0}} = \frac{y'WX\hat{\beta}_W - \frac{(w'y)^2}{w'1}}{y'Wy - \frac{(w'y)^2}{w'1}} \qquad (5)$$

The adjusted multiple determination coefficient for weighted least squares (WLS) is:

$$R_{W,adj}^2 = 1 - (1 - R_W^2)\frac{n-1}{n-p} \qquad (6)$$

Step 0: Set g for the number of groups; set Δ for the difference of estimated coefficients between two iterations; set Stop (i.e., the number of generated PLS-IRRS solutions)

Step 1: Randomly generate weights w_{ik} with $\sum_{k=1}^{g} w_{ik} = 1$ for all $i = 1,...n$.

Do loop

Step 2: PLS path model estimations

Step 2.1: For $k = 1,...,g$, estimate the PLS path model with the w_{ik} weighted observations

Step 2.2: For $k = 1,...,g$, determine the residuals r_{ik} of the estimated models using the unweighted observations

Step 3: For each $i = 1,...n$, compute the squared reciprocal values $1/r_{ik}^2$

Step 4: Let the normed reciprocal values $1/r_{ik}^2$ become the new weights

Step 5: Compare the estimated coefficients with those of the previous iteration.
If the difference is larger than Δ
Go to Step 2
Else
Use the minimum non-weighted absolute residual value to assign each observation to a group of data.

Step 6: Compute the average value of the weighted coefficients of determination R_W^2 to assess and compare the quality of segmentation results.

Stop

Step 7: Select the final segmentation solution based on the maximum R_W^2 value.

Figure 1: The PLS-IRRS Algorithm

Clusterwise regression and PLS segmentation problems are hard to solve due to the target function's possibly large number of the local optimum solutions. To overcome the problem of stopping in a local optimum solution, PLS-IRRS requires conducting several runs with random starting partitions per pre-defined number of segments to ensure obtaining a final solution that is at least close to the optimum segmentation solution (Becker et al., 2013; Sarstedt, Becker, Ringle, & Schwaiger, 2011). Similar concerns and recommendations apply for latent class segmentation (Wedel & Kamakura, 2000). Sarstedt, Becker, et al. (2011) show in their simulations on finite mixture partial least squares segmentation in PLS (FIMIX-PLS; Hahn, Johnson, Herrmann, & Huber, 2002) that 10 (20) runs return the optimum solution with a probability of 80 (90) percent. Since the PLS-IRRS algorithm is very fast, as discussed later, we recommend carrying out at least 10 runs to ensure ending at least close to optimum segmentation solution.

In PLS segmentation, the maximization of the weighted average of segment-specific coefficients of determination R_w^2 represents an appropriate target function (Becker et al., 2013; Ringle et al., 2014; Ringle, Sarstedt, Schlittgen, & Taylor, 2013). Hence, based on the objective function outcome (e.g., the weighted least squares' maximum average R_w^2 value) of all (e.g., 10) PLS-IRRS solutions, one selects the best PLS segmentation for a certain per-specified number of segments.

As in PLS-GAS and other segmentation methods, researchers must pre-specify a number of segments when running PLS-IRRS. The optimum number of segments is usually unknown. One may run FIMIX-PLS (Hahn et al., 2002; Sarstedt & Ringle, 2010) to determine the number of segments and, then, run PLS-IRRS to obtain the final segmentation solution. Alternatively, the systematic selection of the most appropriate number of segments may involve PLS-IRRS runs with different numbers of pre-specified segments (for details on the model selection see Becker, Ringle, Sarstedt, and Völckner (2014) and Sarstedt, Becker, et al. (2011). For these results, the objective function outcome (e.g., the weighted least squares' maximum average R_w^2 value) is one possible strategy to decide on the best-suited number of segments when using PLS-IRRS.

3. Investigation of PLS-IRRS' Behavior

3.1 Design of the Study and Data Generation

The results of a simulation study permit investigating the behavior and performance of PLS-IRRS. For this purpose, we select a simulation design that represents different data constellations that frequently occur in empirical applications. In accordance with prior simulation studies on PLS and PLS segmentation (Becker et al., 2013; Reinartz, Haenlein, & Henseler, 2009; Ringle et al., 2013; Sarstedt, Becker, et al., 2011), we select the subsequent factors and factor levels which closely follow the design presented by Ringle et al. (2014):

Data

- Number of observations [two groups both with 50 observations, two groups both with 100 observations, one group with 50 and another group with 150 observations; three groups with 50 observations each].
- Data distribution of manifest variables [normal, lognormal, and the difference of two independent lognormal distributions].

Segment characteristics

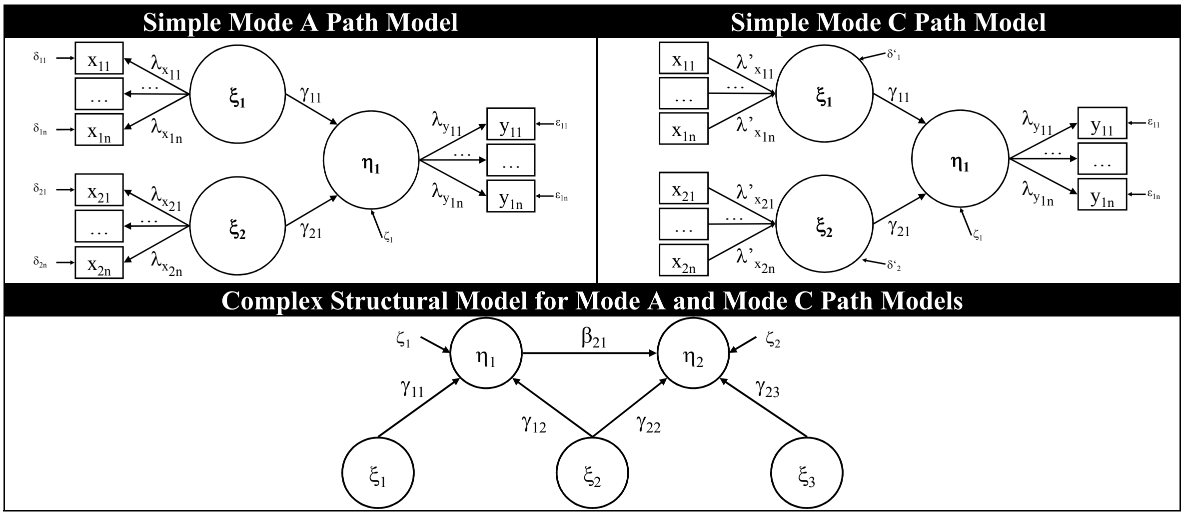
- The number of segments [2, 3].
- The relative segment sizes of the segments [balanced, unbalanced]; see number of observations.

Measurement model

- Outer loadings for Mode A measurement models [high with all outer loadings at 0.95, lower with all outer loadings at 0.75; varied with linearly increasing outer loadings from 0.75 to 0.95]; see Ringle et al. (2014, p. 259) for more details.
- PLS path model constellations [Mode A; Mode C]; see Wold (1982) and Lohmöller (1989) for details on Mode A, Mode B, and Mode C.

Structural Model

- The error variance of the endogenous latent variable [small at 5%; medium at 10%, large at 20%; for two clusters only, mixed at a smaller level with 5% and 10%, for two clusters only, mixed at a larger level with and also 10% and 20%] and, thus, the separability of data in terms of the group-specific difference between identical relationships in the structural model determined by the distance measure *D*; see Ringle et al. (2014) for details on the distance measure.
- Complexity of the PLS path model as shown in Figure 2 [simple path model, complex path model].



Note: See Ringle et al. (2014) for an explanation of symbols.

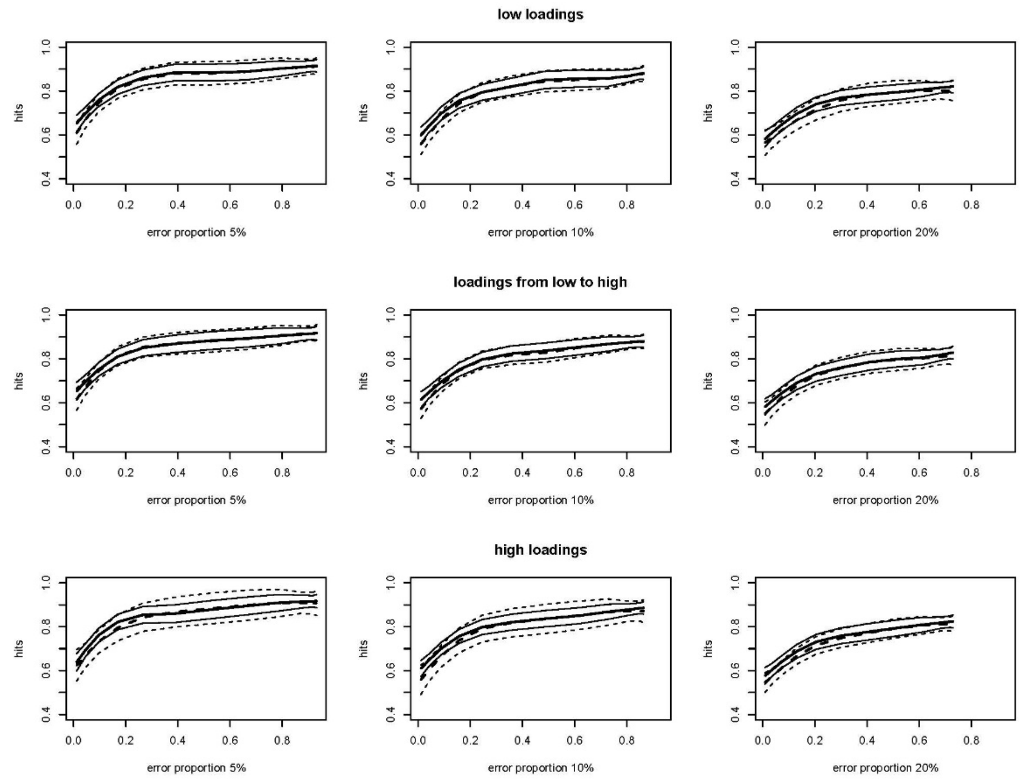
Figure 2: PLS Path Models (Ringle et al., 2014)

To get stable average results, we generate ten data sets for every factor level combination. Hence, we generate $3 \cdot 3 \cdot 3 \cdot 2 \cdot 5 \cdot 2 \cdot 10 = 5{,}400$ data sets for two groups and $1 \cdot 3 \cdot 3 \cdot 2 \cdot 3 \cdot 2 \cdot 10 = 1{,}800$ data sets for three groups which results in a total number of 7,200 data sets used for this simulation study. In accordance, we generate data for each group of data that meet the requirements of the pre-defined factor level combinations. The data generation follows a procedure introduced by Ringle et al. (2014), which delivers sets of data that precisely match the a priori determined specifications (also see Schlittgen, 2011). Moreover, this procedure permits generating data for Mode A and Mode C path models as required by the design of this simulation study.

We run PLS-IRRS for every generated data set of this simulation study. To analyze the performance of PLS-IRRS, we compare its results with those of a benchmark method. There are four main alternative methods for PLS segmentation proposed in the literature: PLS-GAS (Ringle et al., 2014; Ringle et al., 2013), FIMIX-PLS (Hahn et al., 2002; Sarstedt, Becker, et al., 2011), REBUS-PLS (Esposito Vinzi, Trinchera, Squillacciotti, & Tenenhaus, 2008), and PLS-POS (Becker et al., 2013). Ringle, Sarstedt and Schlittgen (Ringle et al., 2014; Ringle et al., 2013) show that PLS-GAS outperforms FIMIX-PLS and REBUS-PLS. Hence, we select PLS-GAS as benchmark method for PLS-IRRS; a comparison with PLS-POS is an interesting avenue of future research. The data generation and the PLS-GAS runs were carried out in GAUSS 9.0 (Aptech, 2012). In addition, we developed and used a GAUSS 9.0 program to run PLS-IRRS for this study.

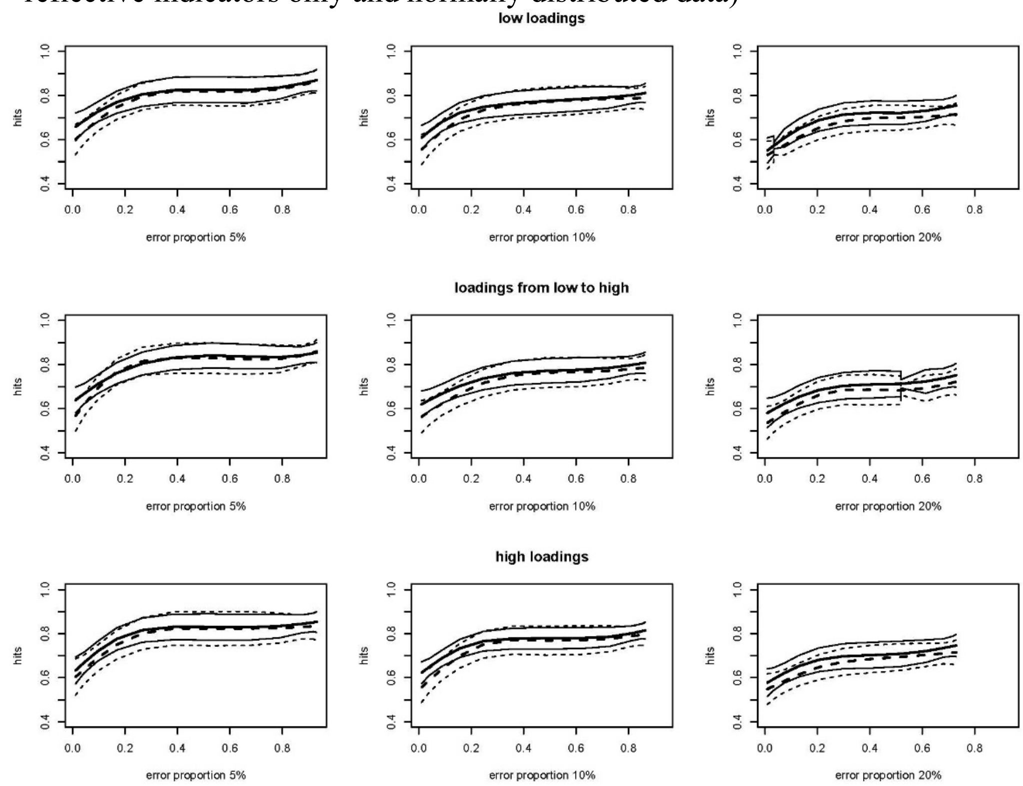
3.2 Results

The analysis results show that PLS-IRRS performs consistently well in all combinations of numbers of observations, numbers of manifest variables in the measurement models, relative segment sizes, levels of outer loadings, and regardless of whether the data are normal or non-normal. In most constellations, PLS-IRRS achieves hit rates well above 80 percent; that is, the method correctly partitions the data according to the data pre-specification. Compared to PLS-GAS, PLS-IRRS achieves the same or higher hit rates across all factor level constellations. This also holds for path models with reflective and formative measurement models in which PLS-GAS achieved comparably low success rates of 60 percent or less. Figures 3 and 4 show the hit rates for two sets of experimental conditions with (1) different loading patterns and (2) varying error variances of the endogenous latent variable.



Notes: x-axis: difference D; y-axis: hits = hit rate; PLS-IRRS results: thick line (95% confidence intervals: thin lines); PLS-GAS results: thick dashed line (95% confidence intervals: thin dashed lines)

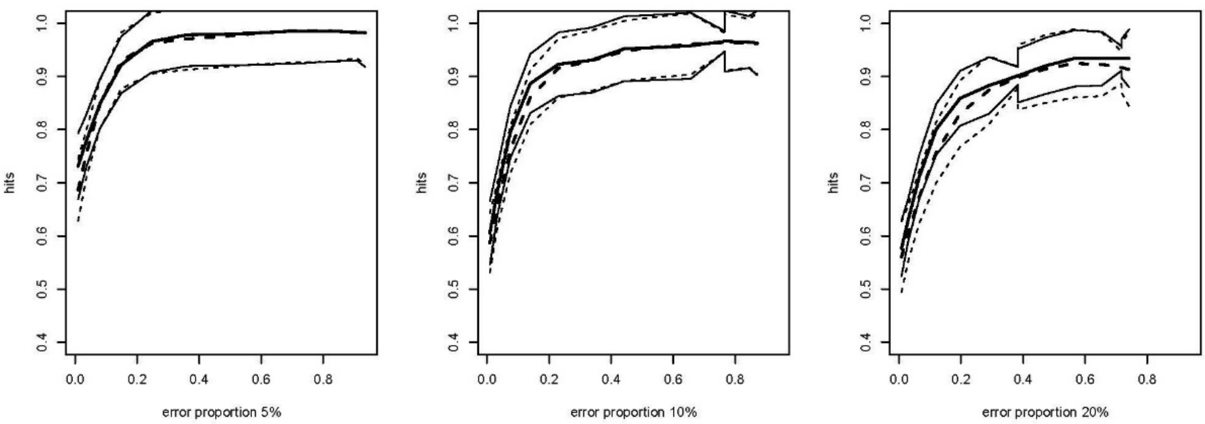
Figure 3: Hit rates for two groups with 100 observations each (simple path model with reflective indicators only and normally distributed data)



Notes: x-axis: difference D; y-axis: hits = hit rate; PLS-IRRS results: thick line (95% confidence intervals: thin lines); PLS-GAS results: thick dashed line (95% confidence intervals: thin dashed lines)

Figure 4: Hit rates for two groups with 50 observations each (simple path model with reflective indicators only and non-normally distributed data)

Figure 5 illustrates the hit rates for a factor constellation with a complex path model with three exogenous and two endogenous constructs (Ringle, Sarstedt and Schlittgen 2014; Ringle, Sarstedt, Schlittgen and Taylor 2013).



Notes: x-axis: difference D; y-axis: hits = hit rate; PLS-IRRS results: thick line (95% confidence intervals: thin lines); PLS-GAS results: thick dashed line (95% confidence intervals: thin dashed lines)

Figure 5: Hit rates for two groups with 50 observations each (complex path model with reflective indicators only and normally distributed data)

In addition, analyzing the adjusted Rand index (ARI; Hubert and Arabi 1985), we find that the ARI values are (1) significantly different from zero in all analyzed situations, (2) slightly increase with higher distances between the group-specific path coefficients, (3) remain at almost similar levels for different levels of pre-specified loadings in the measurement models, and (4) decrease – as expected – with higher levels of error variance. Across all factor level constellations, PLS-IRRS yields higher ARI levels compared to PLS-GAS.

Most importantly, the runtime of PLS-IRRS is much shorter than PLS-GAS. Depending on the experimental condition in the simulation study, the PLS-IRRS method is about 50 to 5,000 times faster than PLS-GAS (Figure 6).

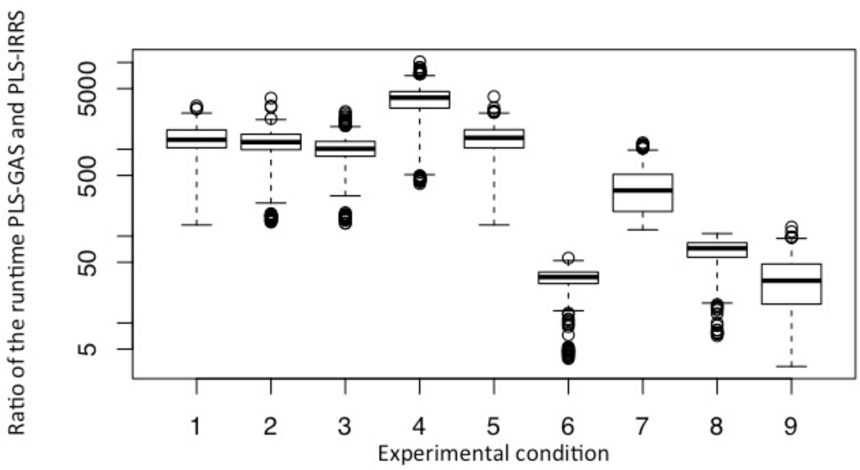


Figure 6: PLS-GAS runtime in relation to PLS-IRRS for nine randomly chosen experimental conditions

To summarize, the results demonstrate the capabilities and effectiveness of PLS-IRRS in various situations encountered in practical applications. PLS-IRRS performs slightly superior compared to PLS-GAS – the primary approach in the field – but at a considerably shorter runtime.

4. Empirical Example

Our empirical illustration employs the ACSI model (Anderson & Fornell, 2000; Fornell, Johnson, Anderson, Cha, & Bryant, 1996), which is one of the most prominent PLS-SEM applications. Prior research used the ACSI model and original data to demonstrate the usefulness of other PLS segmentation methods such as FIMIX-PLS, REBUS-PLS and PLS-GAS (Rigdon, Ringle, Sarstedt, & Gudergan, 2011; Ringle, Sarstedt, & Mooi, 2010; Ringle et al., 2014). For this reason, the model and data are particularly suitable for an application of the new PLS-IRRS method. Since prior research results revealed particular advantageous segmentation results of PLS-GAS compared with alternative PLS segmentation methods (Ringle et al., 2014; Ringle et al., 2013), we select PLS-GAS as the benchmark method for comparing PLS-IRRS' results and computation time needed.

The ACSI model analyses the influence of 'perceived quality', 'perceived value' and 'customer expectations' on 'overall customer satisfaction' and the relationship between 'overall customer satisfaction' and 'customer loyalty' (see Ringle et al., 2014). To provide comparability we employ the same ACSI data as employed by Rigdon et al. (2011); Ringle et al. (2010); Ringle et al. (2014). These authors provide more detailed information on the model and data used.

Parameter estimation on the full data set and on the group models was carried out using SmartPLS 3 (Ringle et al. 2015). Consistent with prior studies, we find that the aggregate PLS-SEM analysis provides reliable and valid measures for the four constructs in our model (see Hair et al., 2014 for details of the PLS-SEM results assessment). In the full data set all paths are significant and positive, but vary in their magnitude from 0.021 (customer expectation on customer satisfaction) to 0.687 (customer satisfaction on customer loyalty).

To estimate the group membership we used GAUSS 12.0 (Aptech, 2012). For the PLS-GAS we used the GAUSS code provided by (Ringle et al., 2014) and for PLS-IRRS we used our own implementation in GAUSS as discussed previously. Both procedures also provide the total time needed for the calculations.

Consistent with prior research we identify two segments as the best PLS-IRRS solution. Using more groups does not improve the weighted average R^2 value of the endogenous constructs and, in addition, using more than three groups provided groups with insufficient group members (i.e., less than 10 observation which would not provide reliable PLS estimates).

As shown in Figure 7, for two groups of data, the group-specific coefficients of PLS-IRRS of most of the paths are significantly different. There are two exceptions: (1) the difference for the paths from customer expectation to customer satisfaction, which is not surprising since each group-specific path (Group 1: 0.004; Group 2: 0.021) is not significantly different from zero ($p > 0.05$); (2) the difference for the paths from perceived quality to perceived value ($\Delta = 0.005$). In terms of significant path relationships, we get a similar picture for the full data model and the group-specific model estimations (i.e., all path coefficients are significant except the customer expectation to customer satisfaction relationship). Yet, the path coefficient's magnitude changes when considering the group-specific heterogeneity in the model. Noteworthy, the path from customer expectation to perceived value, which is small but significantly positive (0.072, $p < 0.01$) in the full data model, changes direction when comparing the two groups (Group 1: -0.133, $p < 0.01$; Group 2: 0.392, $p < 0.01$). The sizes for the two groups are only slightly different from an equal distribution (49.75% and 50.25%). The weighted average R^2 of the group-specific solution improves compared with the full model for two of the four endogenous construct (i.e., perceived quality and perceived value), while it is comparable to the full model for customer satisfaction and customer loyalty. Thus, one can conclude that the PLS-IRRS solution improves the overall model as most group-specific coefficients are significantly different and models' explained variance increases compared to the full data model.

		PLS–IRRS			PLS–GAS		
	Full data set	g = 1	g = 2	$\|\Delta\|^a$	g = 1	g = 2	$\|\Delta\|^a$
Customer satisfaction → customer loyalty	0.687**	0.434**	0.840**	0.406**	0.638**	0.738**	0.099**
Customer expectation → customer satisfaction	0.021**	0.004ns	0.021ns	0.017ns	*-0.006*[ns]	0.049**	0.055**
Customer expectation → perceived quality	0.557**	0.365**	0.811**	0.446**	0.530**	0.642**	0.112**
Customer expectation → perceived value	0.072**	-0.133**	0.392**	0.524**	-0.075**	0.286**	0.361**
Perceived quality → customer satisfaction	0.558**	0.613**	0.535**	0.078**	0.638**	0.477**	0.160**
Perceived quality → perceived value	0.620**	0.490**	0.494**	0.005ns	0.669**	0.545**	0.124**
Perceived value → customer satisfaction	0.394**	0.346**	0.412**	0.066**	0.317**	0.450**	0.133**
	Full data set	g = 1	g = 2	Weighted average	g = 1	g = 2	Weighted average
R^2 customer satisfaction	0.777	0.778	0.776	0.777	0.756	0.804	0.780
R^2 customer loyalty	0.471	0.508	0.436	0.472	0.408	0.544	0.477
R^2 perceived quality	0.310	0.271	0.353	0.312	0.281	0.412	0.348
R^2 perceived value	0.439	0.444	0.440	0.442	0.400	0.579	0.491
Segment size	100%	49.75%	50.25%		49.02%	50.98%	

** = Sig. at 0.01; * = Sig. at 0.05; ns = nonsignificant

[a] PLS-SEM multi-group comparison, the PLS-MGA and Welch-Satterthwait approach have been applied and yield the same results in terms of significance of the differences (Sarstedt, Henseler, et al., 2011).

Figure 7: PLS-GAS and PLS-IRRS Applications to the ACSI Model

We find comparable results for the PLS-GAS procedure. The main difference to the results from the PLS-IRRS procedure is that all differences between groups are significant for PLS-GAS, while two of the differences are not significant for PLS-IRRS. Besides, we obtain similar relative segments sizes and weighted R^2 values, especially for the key target constructs customer satisfaction and customer loyalty. Moreover, a stronger relationship in the first segment of PLS-IRRS also is the stronger path in the PLS-GAS and vice versa. For instance, regarding the customer satisfaction to customer loyalty relationship, both PLS-IRRS and PLS-GAS reveal that the coefficient in Group 1 is weaker than the coefficient in Group 2. The only exception is the path from perceived quality to perceived value where PLS-IRRS does not find a significant difference. Nevertheless, the results are very much comparable and go in the same direction. In general, when reviewing the results of this example, PLS-GAS reveals smaller to average difference for all relationships while PLS-IRRS returns either very strong or very weak (nonsignificant) differences.

To summarize, both methods deliver comparable segmentation results (also compared to previous studies) that would provide similar conclusions about the two data groups. Yet, they diverge strongly in the amount of time used1: PLS-IRRS needed 41 seconds (less than a minute), which included 10 calculation of the algorithm with different starting partitions and choosing the best solution in terms of average weighted R^2. In contrast, ten PLS-GAS calculations with different starting partitions needed 43,696 seconds (roughly 728 minutes) for the first-stage to generate a starting partition and 21859 seconds (roughly 364 minutes) for the second-stage, i.e., the hill-climbing algorithm for local improvement. Hence, even a single PLS-GAS run needed on average more than one and a half hours for both stages (i.e., 109 minutes; ranging from 97 to 120).

In this ACSI model application, the PLS-IRRS is more than 100 times faster than a single run of the PLS-GAS procedure. Such a large difference is important for researchers that want to calculate and compare different models and numbers of segments. Providing similar results in much less time makes the PLS-IRRS desirable for efficient application and acceptance of the method for applied research.

1 We calculated both algorithms on a common personal computer (laptop) usually employed by university staff, with an Intel Core i7 with 2.7 GHz, 8GB RAM and Windows 7 64bit.

5. Summary

This study substantiates that PLS-IRRS returns reliable and valid solutions. Different random starts for the weighting lead to the same solution, which match the expected group-specific outcomes of a-priori generated data sets with pre-defined numbers of segments. Prior research showed that PLS-GAS offers superior results compared with PLS segmentation methods such as FIMIX-PLS and REBUS-PLS (Ringle et al., 2014; Ringle et al., 2013). In comparison with PLS-GAS, PLS-IRRS returns results of similar quality and, likewise, is generally applicable to all kinds of PLS path models. Most important, we find that the PLS-IRRS computations are extremely fast. This is a particularly advantageous characteristic for applications.

The combinations of the general applicability to PLS, the high quality of results and the computational speed justifies the conclusion that PLS-IRRS is superior compared with PLS-GAS but also FIMIX-PLS and REBUS-PLS. When addressing the requirement to assess PLS path modeling results for the critical issue of unobserved heterogeneity to obtain valid results (Becker et al., 2013; Hair et al., 2012), we expect that PLS-IRRS will become the primary methods of choice. Future research, however, should evaluate its performance against the new PLS-POS method (Becker et al., 2013). Moreover, PLS-IRRS fits very well with the new consistent PLS method (PLSc; Dijkstra, 2014; Dijkstra & Henseler, 2015). Hence, we expect that future research will adapt this segmentation approach to PLSc and thereby further proliferate PLS-IRRS' usefulness.

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