Industrial Management & Data Systems

# Gain more insight from your PLS-SEM results: The importance-performance map analysis

Christian M. Ringle Marko Sarstedt

The current issue and full text archive of this journal is available on Emerald Insight at:
**www.emeraldinsight.com/0263-5577.htm**



# Gain more insight from your PLS-SEM results

## The importance-performance map analysis

Christian M. Ringle
*Institute for Human Resource Management and Organizations (HRMO), Hamburg University of Technology Hamburg (TUHH), Hamburg, Germany and Newcastle Business School, University of Newcastle, Newcastle, Australia, and*
Marko Sarstedt
*Faculty of Economics, Otto-von-Guericke University, Magdeburg, Germany and Newcastle Business School, University of Newcastle, Newcastle, Australia*

Received 31 October 2015
Revised 6 January 2016
4 February 2016
Accepted 14 February 2016


### Abstract

**Purpose** – The purpose of this paper is to introduce the importance-performance map analysis (IPMA) and explain how to use it in the context of partial least squares structural equation modeling (PLS-SEM). A case study, drawing on the IPMA module implemented in the SmartPLS 3 software, illustrates the results generation and interpretation.

**Design/methodology/approach** – The explications first address the principles of the IPMA and introduce a systematic procedure for its use, followed by a detailed discussion of each step. Finally, a case study on the use of technology shows how to apply the IPMA in empirical PLS-SEM studies.

**Findings** – The IPMA gives researchers the opportunity to enrich their PLS-SEM analysis and, thereby, gain additional results and findings. More specifically, instead of only analyzing the path coefficients (i.e. the importance dimension), the IPMA also considers the average value of the latent variables and their indicators (i.e. performance dimension).

**Research limitations/implications** – An IPMA is tied to certain requirements, which relate to the measurement scales, variable coding, and indicator weights estimates. Moreover, the IPMA presumes linear relationships. This research does not address the computation and interpretation of non-linear dependencies.

**Practical implications** – The IPMA is particularly useful for generating additional findings and conclusions by combining the analysis of the importance and performance dimensions in practical PLS-SEM applications. Thereby, the IPMA allows for prioritizing constructs to improve a certain target construct. Expanding the analysis to the indicator level facilitates identifying the most important areas of specific actions. These results are, for example, particularly important in practical studies identifying the differing impacts that certain construct dimensions have on phenomena such as technology acceptance, corporate reputation, or customer satisfaction.

**Originality/value** – This paper is the first to offer researchers a tutorial and annotated example of an IPMA. Based on a state-of-the-art review of the technique and a detailed explanation of the method, this paper introduces a systematic procedure for running an IPMA. A case study illustrates the analysis, using the SmartPLS 3 software.


**Keywords** Structural equation modeling (SEM), Partial least squares (PLS), Unified theory of acceptance and use of technology (UTAUT), SmartPLS, Importance-performance map analysis (IPMA)

**Paper type** General review

The authors thank Geoffrey S. Hubona for sending and granting the authors permission to use the data of the study by Al-Gahtani *et al.* (2007). This paper uses the statistical software SmartPLS 3 (www.smartpls.com). Ringle acknowledges a financial interest in SmartPLS.



0263-5577
DOI 10.1108/IMDS-10-2015-0449

## Introduction

Partial least squares structural equation modeling (PLS-SEM; Chin, 1998; Garson, 2014; Hair *et al.*, 2017; Lohmöller, 1989; Rigdon, 2013; Tenenhaus *et al.*, 2005; Wold, 1982) is a variance-based method to estimate path models with latent variables. The PLS-SEM approach is particularly useful when the study's focus is on the analysis of a certain target construct's key sources of explanation. For example, the technology acceptance model (TAM; Davis, 1989; Davis *et al.*, 1989) and its various extensions, such as the unified theory of acceptance and use of technology (UTAUT; Venkatesh *et al.*, 2003), are popular models for PLS-SEM applications in management information systems research. In the marketing field, the American Customer Satisfaction Index (ACSI) model (Anderson and Fornell, 2000; Fornell *et al.*, 1996) is another widespread PLS-SEM application. PLS-SEM enjoys rapidly increasing usage in various business disciplines, such as accounting (Lee *et al.*, 2011), family business (Sarstedt *et al.*, 2014), international business (Richter *et al.*, 2015), management information systems (Ringle *et al.*, 2012), marketing (Hair *et al.*, 2012), operations management (Peng and Lai, 2012), strategic management (Hair *et al.*, 2012a), and tourism research (do Valle and Assaker, 2015).

The purpose of this paper is to explain and illustrate the use of the importance-performance map analysis (IPMA; also called importance-performance matrix, impact-performance map, or priority map analysis), a useful analysis approach in PLS-SEM that extends the standard results reporting of path coefficient estimates by adding a dimension that considers the average values of the latent variable scores. More precisely, the IPMA contrasts the total effects, representing the predecessor constructs' importance in shaping a certain target construct, with their average latent variable scores indicating their performance (Fornell *et al.*, 1996; Martilla and James, 1977; Slack, 1994). The goal is to identify predecessors that have a relatively high importance for the target construct (i.e. those that have a strong total effect), but also have a relatively low performance (i.e. low average latent variable scores).

## Illustrative example

To illustrate the concept of an IPMA, consider the PLS path model in Figure 1 with four constructs $Y_1$-$Y_4$. In this PLS path model, $Y_4$ represents the final target variable,

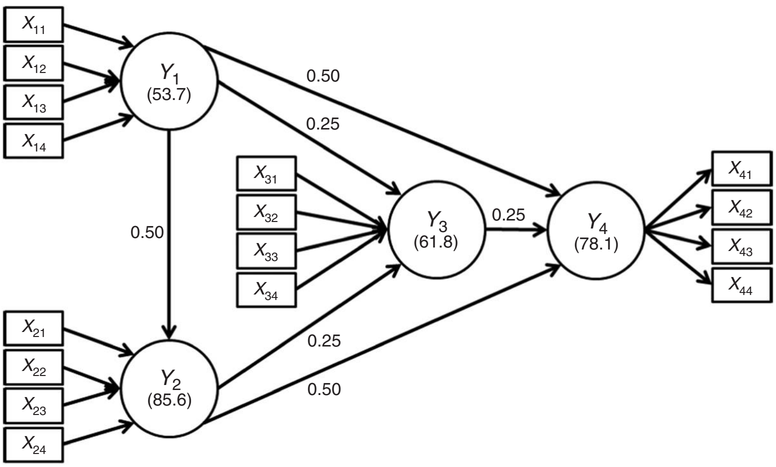



**Figure 1.**
IPMA model

directly predicted by $Y_1$-$Y_3$. Furthermore, $Y_1$ and $Y_2$ have indirect effects on $Y_4$ via $Y_3$. Adding the predecessor constructs' direct and indirect effects yields their total effects on $Y_4$, which represent the importance dimension in the IPMA. In contrast, these constructs' average latent variable scores represent their performance, in the sense that high values indicate a greater performance.

The IPMA combines these two aspects graphically by contrasting the (unstandardized) total effects on the *x*-axis with the latent variable scores, rescaled on a range from 0 to 100, on the *y*-axis. The result is a chart such as in Figure 2. For the results interpretation, we focus on constructs in the lower right area of the importance-performance map. These constructs have a high importance for the target construct, but show a low performance. Consequently, there is a particularly high potential to improve the performance of the constructs positioned in this area.

In Figure 2, $Y_1$ is particularly important to explain the target construct $Y_4$. More precisely, a one-unit point increase in $Y_1$'s performance increases the performance of $Y_4$ by the value of $Y_1$'s total effect on $Y_4$, which is 0.84 (ceteris paribus). Since the performance of $Y_1$ is relatively low, there is substantial room for improvement, making the aspect underlying this construct particularly relevant for managerial actions. While this introductory example shows an IPMA on the construct level, the analysis can also be run on the indicator level. In this case, individual data points in the importance-performance map are derived from indicator mean values and their total effect on a particular target construct.

## The IPMA procedure

PLS-SEM studies that draw on IPMA results offer important insights into the role of antecedent constructs and their relevance for managerial actions (e.g. Grønholdt *et al.*, 2015; Höck *et al.*, 2010; Kristensen *et al.*, 2000; Martensen *et al.*, 2007; Martensen and Grønholdt, 2010). The IPMA also becomes particularly useful when contrasting PLS-SEM results from a multigroup analysis (Hair *et al.*, 2017; Sarstedt *et al.*, 2011), as several studies illustrate (Rigdon *et al.*, 2011; Schloderer *et al.*, 2014; Völckner *et al.*, 2010). However, to date, no comprehensive tutorial highlights the requirements for using the method, or offers a step-by-step introduction to its use. Against this background, this paper presents a state-of-the-art review and detailed explanation of

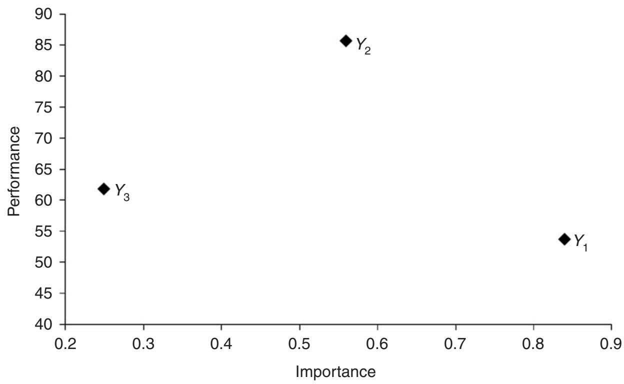



**Figure 2.** Importance-performance map of the target construct $Y_4$

the IPMA. A case study on the TAM illustrates the analysis, using the SmartPLS 3 (Ringle *et al.*, 2015) software. The paper explains an IPMA by following the five-step procedure as shown in Figure 3.

When using an IPMA, the first step involves checking if the requirements for carrying out the analysis have been fulfilled (Step 1). The analysis proceeds with the computation of the latent variables' performance values (Step 2) and their importance values (Step 3). The importance-performance map creation for a selected target construct is based on these results (Step 4). Finally, the IPMA can be extended on the indicator level to obtain more specific information on the most effective managerial actions (Step 5). The following sections explain each step in greater detail.

## Step 1: requirements check

IPMA applications have to meet three requirements. First, the rescaling of the latent variable scores on a range from 0 to 100 requires all indicators in the PLS path model to use a metric or quasi-metric scale (Sarstedt and Mooi, 2014). Second, all the indicator coding must have the same scale direction. The minimum value of an indicator must represent the worst outcome and the maximum value must represent the best outcome of an indicator. Otherwise, we cannot conclude that higher latent variable scores represent better performance. If the indicator coding has a different direction compared to the other indicators in the measurement model (i.e. a high value represents a negative outcome), we must rescale the indicator. In this case, the indicator coding needs to be changed by reversing the scale (e.g. on a five-point scale, 5 becomes 1 and 1 becomes 5, 4 becomes 2 and 2 becomes 4, and 3 remains unchanged). Third, regardless of the measurement model being formatively or reflectively specified, the outer weights estimates must be positive. If the outer weights are negative, the latent variable scores will not fall within the 0-100 range, but would, for example, be between −5 and 95. Note that there are different reasons for (unexpected) negative outer weights. If an outer weight is negative and significant, the researcher should inspect the indicator and its scale. It may have another direction compared to the other indicators in the measurement model, which requires reversing the scale. In case of non-significant outer weights (with negative signs), the researcher may consider removing those indicators. Finally, negative outer weights might be a result of high indicator collinearity. For example, variance inflation factor values of 5 and higher indicate a potential collinearity problem (Hair *et al.*, 2017). In this case, the researcher may also consider removing indicators. However removing indicators from measurement models involves some additional considerations as explained by Hair *et al.* (2017; see Chapter 5) in more detail.

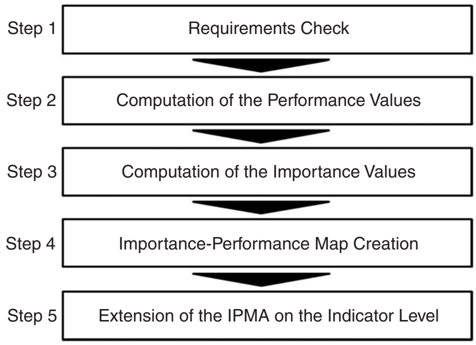



**Figure 3.**
Steps of the importance-performance map analysis

While not being a formal requirement for running an IPMA, researchers should carefully consider PLS path model set-ups that favor IPMA use on the indicator level. When a latent variable of high priority for a specific target construct is identified, it is particularly advantageous to further analyze this predecessor construct's measurement model on the indicator level. Such an assessment is particularly useful when the measurement model is specified as formative – as is the case in our sample model in Figure 1. In this case, the indicators describe aspects that shape the corresponding construct, while their weights indicate each aspect's importance in this respect. Therefore, aspects underlying indicators with high weights should be given more attention to identify managerial actions aiming to improve the target construct's performance – see Höck *et al.* (2010) for an application. Note that the IPMA can be applied on any kind of PLS path model, regardless of whether the researcher specifies latent variables' measurement models as formative or reflective. The IPMA builds on the outer weights – as explained in more detail in the subsequent sections – and PLS-SEM always provides outer weights estimates, also when a measurement model is specified as reflective. In this context, it is important to note that the distinction between reflectively and formatively specified constructs refers to the ways how researchers develop proxies for conceptual variables and the resulting measurement approaches. While PLS-SEM readily processes reflectively and formatively specified constructs, it does so by linearly combining indicators to form composite variables. These composite variables are treated as proxies of the concepts under investigation (Rigdon, 2012, 2014) and serve as input for the IPMA in Step 2 (Figure 3). To represent formative measurement models, PLS-SEM draws on composite indicators – as opposed to causal indicators – which fully form the latent variable without an error term on the construct level (Bollen and Bauldry, 2011; Bollen and Diamantopoulos, in press). At the same time, PLS-SEM only approximates measures in reflective measurement models that draw on a factor model logic (Sarstedt *et al.*, 2016). While the "bias" that PLS-SEM produces when estimating common factor models is very small – provided that measurement models meet minimum recommended standards in terms of the number of indicators and indicator loadings – recent research has also introduced the consistent PLS approach that handles common factor model-based measures without limitations (Dijkstra and Henseler, 2015). Acknowledging the proxy character of the method (Rigdon, 2012; Sarstedt *et al.*, 2016), the following sections refer to the common denotation of reflective and formative measurement models and their standard treatment in PLS-SEM analyses.

**Step 2: computation of the performance values**

The indicator data determines the latent variable scores and, thus, their performance. Similarly, when conducting an IPMA on the indicator level, the mean value of an indicator represents its average performance. When computing average values on the construct or indicator level, it is important to remember that indicators may be measured on different scales. For examples, some indicators may use a scale with values from 1 to 5, while others use a scale with values from 1 to 7, or from 1 to 9. To facilitate the interpretation and comparison of performance levels, the IPMA rescales indicator scores on a range between 0 and 100, with 0 representing the lowest and 100 representing the highest performance. Since most researchers are familiar with interpreting percentage values, this kind of performance scale is easy to understand. The rescaling of an observation $j$ with respect to indicator $i$ proceeds via:

$$x_{ij}^{\text{rescaled}} = \frac{E[x_{ij}] - \min[x_i]}{\max[x_i] - \min[x_i]} \cdot 100, \tag{1}$$

where $x_i$ is the $i$th indicator in the PLS path model; E[.] represents indicator $i$'s actual score of respondent $j$, min[.] and max[.] represent the indicator's minimum and maximum value. It is important to note that the minimum and maximum values refer to the potential values on a certain scale (e.g. 1 and 5 on a 1-5 scale) and not the minimum and maximum values of the actual responses (e.g. 2 and 4 on a 1-5 scale). Hence, if respondents use lowest actual response is 2 but the scale has a minimum value of 1, it is mandatory to use the 1 as minimum value for rescaling. For example, according to this formula, a value of 4 on a 1-5 scale becomes $(4-1)/(5-1)\cdot 100=75$ while a 4 on a 1-7 scale becomes $(4-1)/(7-1)\cdot 100=50$. All data points used for estimating the PLS path model are rescaled this way.

Table I shows an excerpt of the original indicator data ($n=300$) used to estimate the sample model from Figure 1. All indicators are measured on a scale from 1 to 5. Table II shows the indicator data from Table I, rescaled on a range from 0 to 100, which serve as input for the computation of the rescaled latent variable scores. In addition, the mean values of the rescaled indicators represent their performance values (e.g. 79 for indictor $x_{11}$ and 77.5 for indicator $x_{12}$), which are later used for the IPMA on the indicator level.

The rescaled latent variable scores are a linear combination of the rescaled indicator data and the rescaled outer weights – regardless whether the measurement model of a latent variable is reflective (i.e. $Y_4$) or formative (i.e. $Y_1$-$Y_3$). To obtain the rescaled weights, we must first compute the unstandardized weights by dividing the standardized weights by the standard deviation of its respective indicator.

| Case | $x_{11}$ | $x_{12}$ | $x_{13}$ | $x_{14}$ | $x_{21}$ | $x_{22}$ | $x_{23}$ | $x_{24}$ | $x_{31}$ | $x_{32}$ | $x_{33}$ | $x_{34}$ | $x_{41}$ | $x_{42}$ | $x_{43}$ | $x_{44}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 5 | 2 | 1 | 5 | 3 | 3 | 4 | 5 | 5 | 2 | 4 | 3 | 1 | 2 | 4 | 3 |
| 2 | 4 | 5 | 2 | 3 | 5 | 4 | 5 | 3 | 4 | 1 | 1 | 2 | 3 | 5 | 4 | 3 |
| 3 | 4 | 1 | 3 | 4 | 5 | 3 | 4 | 5 | 5 | 3 | 5 | 3 | 3 | 5 | 3 | 1 |
| 4 | 1 | 3 | 2 | 1 | 3 | 2 | 2 | 4 | 1 | 4 | 1 | 3 | 5 | 1 | 4 | 4 |
| 5 | 3 | 2 | 1 | 3 | 5 | 1 | 2 | 3 | 5 | 2 | 2 | 3 | 1 | 3 | 4 | 5 |
| … | … | … | … | … | … | … | … | … | … | … | … | … | … | … | … | … |
| 299 | 2 | 4 | 3 | 4 | 4 | 3 | 3 | 4 | 4 | 2 | 2 | 1 | 2 | 5 | 4 | 3 |
| 300 | 2 | 4 | 3 | 1 | 5 | 2 | 3 | 5 | 1 | 1 | 4 | 3 | 4 | 2 | 1 | 5 |
| Mean value | 4.2 | 4.1 | 3.4 | 2.3 | 3.6 | 4.5 | 3.4 | 3.1 | 3.4 | 4.7 | 4.4 | 4.6 | 3.4 | 4.2 | 4.5 | 4.2 |

**Table I.**
Original indicator data

| Case | $x_{11}$ | $x_{12}$ | $x_{13}$ | $x_{14}$ | $x_{21}$ | $x_{22}$ | $x_{23}$ | $x_{24}$ | $x_{31}$ | $x_{32}$ | $x_{33}$ | $x_{34}$ | $x_{41}$ | $x_{42}$ | $x_{43}$ | $x_{44}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 100 | 25 | 0 | 100 | 100 | 25 | 75 | 50 | 50 | 50 | 75 | 100 | 0 | 25 | 75 | 50 |
| 2 | 75 | 100 | 25 | 50 | 75 | 0 | 0 | 25 | 100 | 75 | 100 | 50 | 50 | 100 | 75 | 50 |
| 3 | 75 | 0 | 50 | 75 | 100 | 50 | 100 | 50 | 100 | 50 | 75 | 100 | 50 | 100 | 50 | 0 |
| 4 | 0 | 50 | 25 | 0 | 0 | 75 | 0 | 50 | 50 | 25 | 25 | 75 | 100 | 0 | 75 | 75 |
| 5 | 50 | 25 | 0 | 50 | 100 | 25 | 25 | 50 | 100 | 0 | 25 | 50 | 0 | 50 | 75 | 100 |
| … | … | … | … | … | … | … | … | … | … | … | … | … | … | … | … | … |
| 299 | 25 | 75 | 50 | 75 | 75 | 25 | 25 | 0 | 75 | 50 | 50 | 75 | 25 | 100 | 75 | 50 |
| 300 | 25 | 75 | 50 | 0 | 0 | 0 | 75 | 50 | 100 | 25 | 50 | 100 | 75 | 25 | 0 | 100 |
| Mean value | 79.0 | 77.5 | 59.5 | 33.5 | 66.0 | 87.5 | 59.5 | 53.0 | 59.5 | 91.5 | 85.5 | 90.0 | 59.5 | 79.0 | 88.5 | 79.0 |

**Table II.**
Rescaled indicator data

While the standardized outer weights originate from the standard PLS path model estimation, the estimation of each indicator's standard deviation is based on the original indicator data. For example, if $x_{11}$ has a standardized weight of 0.2 and a standard deviation of 1.619, the resulting unstandardized weight is 0.124. Table III shows the (standardized and unstandardized) indicator weights along with the indicators' standard deviations with regard to our sample model in Figure 1.

Finally, we rescale the unstandardized outer weights so that their sum equals one per measurement model. For this purpose, we need to divide each indicator's unstandardized weight (e.g. 0.124 for indicator $x_{11}$) by the sum of the unstandardized weights of all the indicators that belong to the same measurement model. For $Y_1$, the sum of all the unstandardized indicator weights is $0.124+0.168+0.191+0.406=0.889$. Therefore, for indicator $x_{11}$, we obtain the unstandardized and rescaled outer weight of 0.139 after dividing 0.124 by 0.889. The final column in Table III shows the results of the rescaled outer weights.

In the next step, the IPMA uses the rescaled indicator data (Table II) and the rescaled outer weights (Table III) to compute the rescaled latent variable scores by means of simple linear combinations. For example, the first data point in the vector of $Y_1$'s scores is:

$$100 \cdot 0.139+25 \cdot 0.189+0 \cdot 0.215+100 \cdot 0.457 \approx 64.3. \tag{2}$$

Table IV shows the resulting latent variable scores along with their mean values. In our example, $Y_1$ has a mean value (i.e. performance) of 53.7, $Y_2$ of 85.6, $Y_3$ of 61.8, and $Y_4$ of 78.1. These results serve as input for the importance-performance map's performance dimension.

### Step 3: computation of the importance values

A construct's importance in terms of predicting another directly or indirectly linked (target) construct in the structural model is derived from the total effect of the relationship between these two constructs. The total effect is the sum of the direct and

| Latent variable | Indicator | Standardized outer weights | SD of the indicators | Unstandardized outer weights | Rescaled outer weights |
|---|---|---|---|---|---|
| $Y_1$ | $x_{11}$ | 0.2 | 1.619 | 0.124 | 0.139 |
| | $x_{12}$ | 0.3 | 1.789 | 0.168 | 0.189 |
| | $x_{13}$ | 0.4 | 2.099 | 0.191 | 0.215 |
| | $x_{14}$ | 0.5 | 1.231 | 0.406 | 0.457 |
| $Y_2$ | $x_{21}$ | 0.1 | 2.099 | 0.048 | 0.114 |
| | $x_{22}$ | 0.1 | 1.101 | 0.091 | 0.218 |
| | $x_{23}$ | 0.4 | 3.357 | 0.119 | 0.285 |
| | $x_{24}$ | 0.4 | 2.504 | 0.160 | 0.383 |
| $Y_3$ | $x_{31}$ | 0.1 | 1.762 | 0.057 | 0.136 |
| | $x_{32}$ | 0.1 | 1.744 | 0.057 | 0.137 |
| | $x_{33}$ | 0.4 | 2.270 | 0.176 | 0.422 |
| | $x_{34}$ | 0.4 | 2.653 | 0.151 | 0.361 |
| $Y_4$ | $x_{41}$ | 0.3 | 2.164 | 0.139 | 0.186 |
| | $x_{42}$ | 0.3 | 1.874 | 0.160 | 0.215 |
| | $x_{43}$ | 0.3 | 1.413 | 0.212 | 0.286 |
| | $x_{44}$ | 0.3 | 1.291 | 0.232 | 0.313 |

**Table III.** Computation of unstandardized and rescaled outer weights all the indirect effects in the structural model (Hair *et al.*, 2017). For example, to determine the total effect of $Y_1$ on $Y_4$ (Figure 1), we have to consider the direct effect of the relationship between these two constructs (0.50) and the following three indirect effects via $Y_2$ and $Y_3$, respectively:

$$Y_1 \rightarrow Y_2 \rightarrow Y_4 = 0.50 \cdot 0.50 = 0.25$$
$$Y_1 \rightarrow Y_2 \rightarrow Y_3 \rightarrow Y_4 = 0.50 \cdot 0.25 \cdot 0.25 = 0.03125$$
$$Y_1 \rightarrow Y_3 \rightarrow Y_4 = 0.25 \cdot 0.25 = 0.0625$$

Adding up the individual indirect effects yields the total indirect effect of $Y_1$ on $Y_4$, which is approximately 0.34. The total effect of $Y_1$ on $Y_4$ is 0.84 ($= 0.50 + 0.34$), which expresses $Y_1$'s importance in predicting the target construct $Y_4$. Since total effects represent the sum of direct and indirect effects, the IPMA's importance dimension supports the interpretation of complex models including meditators or even multiple mediators.

The IPMA draws on unstandardized effects to facilitate a ceteris paribus interpretation of predecessor constructs' impact on the target construct. This interpretation of the unstandardized effects is analogous to that of unstandardized weights in OLS regression models (Hair *et al.*, 2010). More precisely, by drawing on unstandardized effects, we can conclude that an increase in a certain predecessor construct's performance would increase the target construct's performance by the size of its unstandardized total effect. To determine the significance of the total effects – for example, by means of bias-corrected and accelerated (BCa) confidence intervals (Hair *et al.*, 2017) – researchers need to run the bootstrapping routine. While a non-significant effect provides evidence that a total effect is zero in the population, researchers should retain the corresponding construct in the IPMA since this outcome may also represent a valuable finding (e.g. a company invests into the performance of a construct that has no effect), which also can change with different data, for instance, in alternative contexts of the analysis.

Table V summarizes all the total effects with respect to our target construct $Y_4$. Note that $Y_3$ does not have an indirect effect on $Y_4$; therefore, its total effect equals the direct effect of 0.25. At this point, after computing the importance and performance values, all information required to draw the importance-performance map is available.

Finally, the IPMA also supports path models with moderators. However, if one path relationship in a total effect is moderated, the interpretation of the total effect changes. More precisely, the path coefficient estimate of a moderated effect expresses the strength of the relationship between the two constructs when the moderator variable

| | $Y_1$ | $Y_2$ | $Y_3$ | $Y_4$ |
|---|---|---|---|---|
| 1 | 64.3 | 76.3 | 63.3 | 42.5 |
| 2 | 57.6 | 75.4 | 18.2 | 67.9 |
| 3 | 55.5 | 82.0 | 76.5 | 45.1 |
| 4 | 14.8 | 47.0 | 26.9 | 63.5 |
| 5 | 34.5 | 37.7 | 43.3 | 63.5 |
| … | … | … | … | … |
| 299 | 62.7 | 62.4 | 22.9 | 63.3 |
| 300 | 28.4 | 69.4 | 47.1 | 50.6 |
| Mean value | 53.7 | 85.6 | 61.8 | 78.1 |

**Table IV.** Computation of the rescaled latent variable scores has the value 0 in case researchers follow standard procedure and standardize the moderator's indicators prior to the analysis (for more details see Hair *et al.*, 2017). This interpretation, however, complicates any comparison of total effects that include moderating effects with those that lack a moderating effect. With multiple moderators in a total effect or moderated mediation effect, the interpretation of IPMA's importance dimension becomes difficult. Therefore, we generally advise against the inclusion of moderators in an IPMA.

### Step 4: importance-performance map creation

The IPMA focuses on one key target construct of interest in the PLS path model. Therefore, the first step in creating an importance-performance map requires selecting the target construct of interest. In our example, $Y_4$ represents such a key target construct (Figure 1). The importance and performance values of $Y_4$'s predecessor constructs (i.e. $Y_1$-$Y_3$) allow creating the importance-performance map of $Y_4$. Table VI summarizes the values of this map's importance and performance dimensions – as obtained by the previous IMPA steps.

Scatter plotting the information shown in Table VI allows us to create an importance-performance map as shown in Figure 2 at the beginning of this paper. The *x*-axis represents the importance of $Y_1$-$Y_3$ for explaining the target construct $Y_4$, while the *y*-axis depicts the performance of $Y_1$-$Y_3$ in terms of their average rescaled latent variable scores. For a better orientation, researchers may also draw two additional lines in the importance-performance map: the mean importance value (i.e. a vertical line) and the mean performance value (i.e. a horizontal line) of the displayed constructs (Figure 4). With regard to our example, $Y_1$-$Y_3$ have a mean importance of 0.55 and a mean performance of 67.0 (Table VI). These two additional lines divide the importance-performance map into four areas with importance and performance values below and above the average. Generally, when analyzing the importance-performance map, constructs in the lower right area (i.e. above average importance and below average performance) are of highest interest to achieve improvement, followed by the higher right, lower left and, finally, the higher left areas. Thereby, the importance-performance map provides guidance for the prioritization

| Predecessor construct | Direct effect on $Y_4$ | Indirect effect on $Y_4$ | Total effect on $Y_4$ | Are the total effects on $Y_4$ significant? |
|---|---|---|---|---|
| $Y_1$ | 0.50 | 0.34 | 0.84 | Yes |
| $Y_2$ | 0.50 | 0.06 | 0.56 | Yes |
| $Y_3$ | 0.25 | – | 0.25 | Yes |

**Notes:** All effects denote unstandardized effects. Significance testing uses the bootstrapping routine with 5,000 sample and no sign changes for determining the 95 percent BCa confidence intervals

**Table V.** Direct, indirect, and total effects in the IPMA

| | Importance | Performance |
|---|---|---|
| $Y_1$ | 0.84 | 53.7 |
| $Y_2$ | 0.56 | 85.6 |
| $Y_3$ | 0.25 | 61.8 |
| Mean value | 0.55 | 67.0 |

**Table VI.** Data of the importance-performance map for construct $Y_4$

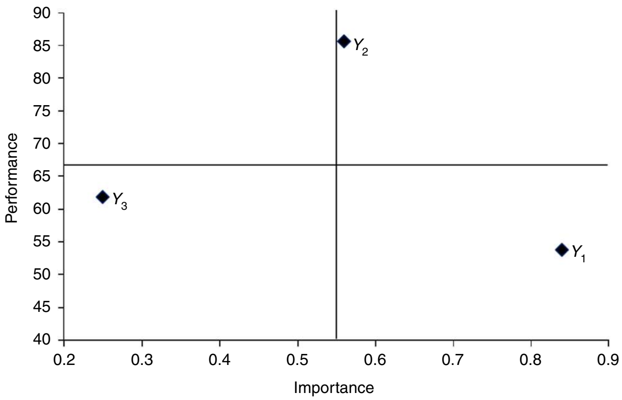



**Figure 4.** Adjusted importance-performance map of the target construct $Y_4$

of managerial activities of high importance for the aspect underlying the selected target, but which require performance improvements.

In our example, the importance-performance map (Figure 4) shows that $Y_1$ has a relatively low performance of 53.7. In comparison with the other constructs, $Y_1$'s performance is slightly below average. On the other hand, with a total effect of 0.84, this construct's importance is particularly high. Therefore, a one-unit increase in $Y_1$'s performance from 53.7 to 54.7 would increase the performance of $Y_4$ by 0.84 points from 78.10 to 78.94. Hence, when managers aim at increasing the performance of the target construct $Y_4$, their first priority should be to improve the performance of aspects captured by $Y_1$, as this construct has the highest (above average) importance, but a relatively low (below average) performance. Aspects related to constructs $Y_2$ and $Y_3$ follow as a second and third priority.

## Step 5: extension of the IPMA on the indicator level

The IPMA is not limited to the construct level. We can also conduct an IPMA on the indicator level to identify relevant and even more specific areas of improvement. More precisely, we can interpret the rescaled outer weights – as reported in formative measurement models – as an indicator's relative importance compared to that of the other indicators in a specific measurement model. Alternatively, the interpretation of the indicators' relative contribution can also draw on reflective measurement models but use the outer weights instead of the outer loadings. While the outer weights play no role in the assessment of the reflective measurement model's reliability and validity, they still represent each indicator's contribution to forming the composite variable that represents the construct in the PLS path model.

The importance values are derived from the indicators' total effects on the target construct, which is the result of multiplying the rescaled outer weights of a predecessor construct's indicators with its unstandardized total effect on the target construct. For example, with regard to the indicators of $Y_1$, we would multiply the rescaled outer weights of $x_{11}$-$x_{14}$ (i.e. 0.139, 0.189, 0.215, 0.457; Table III) with the unstandardized total effect of $Y_1$ on $Y_4$ in the structural model (i.e. 0.84). This analysis yields importance values of $x_{11}$-$x_{14}$ of, respectively, 0.117, 0.159, 0.181, and 0.384. The performance values are derived from the indicators' mean value of the rescaled data (i.e. 79, 77.5, 59.5, and 33.5; Table II). With this data for all indicators of $Y_1$, $Y_2$, and $Y_3$, we can create an importance-performance map as shown in Figure 5. In this figure, rectangles represent the indicators of $Y_1$, diamonds those of $Y_2$, and triangles those of $Y_3$.

Derived from this example, indicator $x_{14}$ should have the highest priority for improvement, since it has the highest relative importance, but the lowest performance. A one-unit point increase in $x_{14}$'s performance increases the performance of $Y_4$ by $x_{14}$'s importance value, which is 0.384 (ceteris paribus). Indicators $x_{24}$, $x_{13}$, $x_{23}$, and $x_{12}$ follow with second to fifth priority. The other indicators shown in Figure 5 are less relevant for improving $Y_4$'s performance.

## Empirical example

Investigating the user acceptance and usage of new IT is a perennial theme in mainstream MIS research. Path models explicating IT user acceptance, such as the TAM (Davis, 1989) and its extensions, for example, the UTAUT (Venkatesh *et al.*, 2003), are well known and have been extensively researched. In the light of the method's prediction orientation, researchers usually use PLS-SEM to estimate such models. However, despite PLS-SEM's popularity in this respect, prior research has not, to our best knowledge, yet applied the IPMA in this context. Researchers have thus missed an opportunity to use the available data to gain additional results and findings with which to enrich their conclusions.

In order to demonstrate the efficacy of the IPMA, we draw on data from a survey sample by Al-Gahtani *et al.* (2007) of 722 knowledge workers in Saudi Arabia voluntarily using desktop computer applications. These data were initially analyzed within the context of a modified UTAUT model that synthesized model elements from various other precedent user acceptance models, such as TAM and its extensions (e.g. TAM 2; Venkatesh and Davis, 2000). UTAUT postulates that four constructs act as determinants of behavioral intentions (BIs) to use and actual usage behavior: performance expectancy (PE) (i.e. the degree to which individuals believe that using the system will help them attain improved job performance), effort expectancy (EE) (i.e. the degree of ease associated with the use of the system), subjective norm (SN) (i.e. the degree to which individuals perceive that important others believe they should use computers), and facilitating conditions (FC) (i.e. the degree to which individuals believe that an organizational and technical infrastructure supports the use of the system). Figure 6 shows the model and the PLS-SEM results when using the empirical data and SmartPLS 3 software[1].

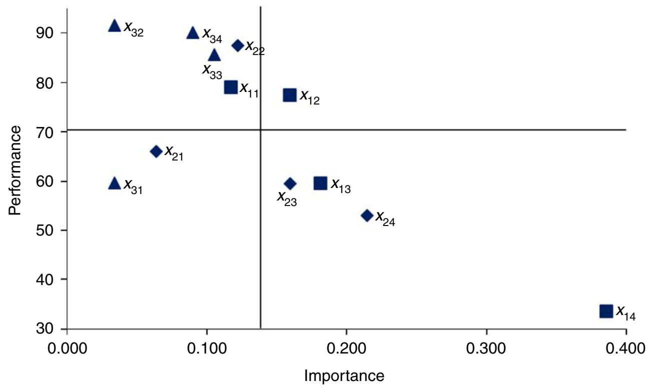



**Figure 5.**
Adjusted importance-performance map of $Y_1$, $Y_2$, and $Y_3$'s indicators on the target construct $Y_4$

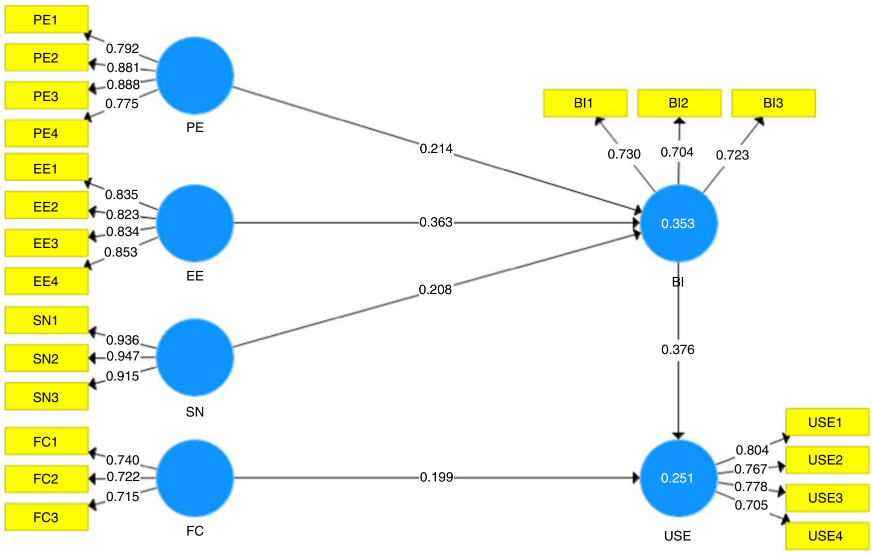



**Figure 6.**
UTAUT model and PLS-SEM results

The evaluation of the measurement models by means of standard evaluation criteria (e.g. Chin, 1998, 2010; Hair *et al.*, 2011, 2013; Henseler *et al.*, 2012, 2017; Roldán and Sánchez-Franco, 2012; Tenenhaus *et al.*, 2005) supports the measures' reliability and validity. This also holds for discriminant validity assessment using Henseler *et al.*'s (2015) recently proposed HTMT criterion, which extends the standard measures used in Al-Gahtani *et al.* (2007). The results from bootstrapping with 5,000 samples using the no sign change option and the 95 percent BCa confidence intervals (Hair *et al.*, 2017) show that all the path coefficients are statistically significant. More specifically, PE, EE, and SN each have significant and positive effects on the BI to use the system. Similarly, the BI and FC each have significant and positive effects on the use behavior (USE). In addition, the bootstrapping results also substantiate that all total effects on the target construct USE are significant.

As a point of departure, we check the requirements for carrying out an IPMA (Step 1). After reviewing the questionnaire, we find that the indicator data are mostly on an interval scale from 1 to 7, in some cases from 0 to 6, and in others from 0 to 11. In respect of all the indicators, a higher value represents a better outcome (for the description of indicators, see Tables III-V in Al-Gahtani *et al.*, 2007). We, therefore, do not need to reverse the scale of any of the indicators. When double clicking on the data set in the SmartPLS Project Explorer (Figure 7), the data view opens (Figure 8), which

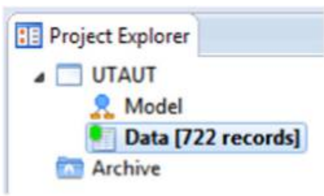
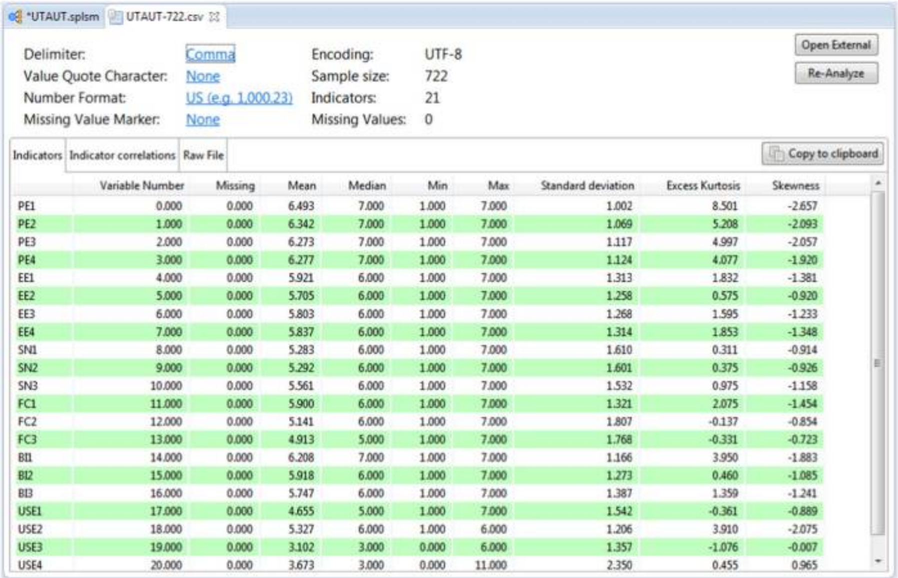



**Figure 7.**
SmartPLS project explorer




| | Variable Number | Missing | Mean | Median | Min | Max | Standard deviation | Excess Kurtosis | Skewness |
|---|---|---|---|---|---|---|---|---|---|
| PE1 | 0.000 | 0.000 | 6.493 | 7.000 | 1.000 | 7.000 | 1.002 | 8.501 | -2.657 |
| PE2 | 1.000 | 0.000 | 6.342 | 7.000 | 1.000 | 7.000 | 1.069 | 5.208 | -2.093 |
| PE3 | 2.000 | 0.000 | 6.273 | 7.000 | 1.000 | 7.000 | 1.117 | 4.997 | -2.057 |
| PE4 | 3.000 | 0.000 | 6.277 | 7.000 | 1.000 | 7.000 | 1.124 | 4.077 | -1.920 |
| EE1 | 4.000 | 0.000 | 5.921 | 6.000 | 1.000 | 7.000 | 1.313 | 1.832 | -1.381 |
| EE2 | 5.000 | 0.000 | 5.705 | 6.000 | 1.000 | 7.000 | 1.258 | 0.575 | -0.920 |
| EE3 | 6.000 | 0.000 | 5.803 | 6.000 | 1.000 | 7.000 | 1.268 | 1.595 | -1.233 |
| EE4 | 7.000 | 0.000 | 5.837 | 6.000 | 1.000 | 7.000 | 1.314 | 1.853 | -1.348 |
| SN1 | 8.000 | 0.000 | 5.283 | 6.000 | 1.000 | 7.000 | 1.610 | 0.311 | -0.914 |
| SN2 | 9.000 | 0.000 | 5.292 | 6.000 | 1.000 | 7.000 | 1.601 | 0.375 | -0.926 |
| SN3 | 10.000 | 0.000 | 5.561 | 6.000 | 1.000 | 7.000 | 1.532 | 0.975 | -1.158 |
| FC1 | 11.000 | 0.000 | 5.900 | 6.000 | 1.000 | 7.000 | 1.321 | 2.075 | -1.454 |
| FC2 | 12.000 | 0.000 | 5.141 | 6.000 | 1.000 | 7.000 | 1.807 | -0.137 | -0.854 |
| FC3 | 13.000 | 0.000 | 4.913 | 5.000 | 1.000 | 7.000 | 1.768 | -0.331 | -0.723 |
| BI1 | 14.000 | 0.000 | 6.208 | 7.000 | 1.000 | 7.000 | 1.166 | 3.950 | -1.883 |
| BI2 | 15.000 | 0.000 | 5.918 | 6.000 | 1.000 | 7.000 | 1.273 | 0.460 | -1.085 |
| BI3 | 16.000 | 0.000 | 5.747 | 6.000 | 1.000 | 7.000 | 1.387 | 1.359 | -1.241 |
| USE1 | 17.000 | 0.000 | 4.655 | 5.000 | 1.000 | 7.000 | 1.542 | -0.361 | -0.889 |
| USE2 | 18.000 | 0.000 | 5.327 | 6.000 | 1.000 | 6.000 | 1.206 | 3.910 | -2.075 |
| USE3 | 19.000 | 0.000 | 3.102 | 3.000 | 0.000 | 6.000 | 1.357 | -1.076 | -0.007 |
| USE4 | 20.000 | 0.000 | 3.673 | 3.000 | 0.000 | 11.000 | 2.350 | 0.455 | 0.965 |

**Figure 8.**
SmartPLS data view

provides further information on the data set (e.g. the missing value marker) and some descriptive statistics of the indicators.

Next, we inspect the signs of the outer weights. After running the PLS-SEM algorithm, SmartPLS opens the Results Report, which also displays the weights of all the indicators. All the outer weight signs are positive. Therefore, in line with IPMA Step 1, all the requirements for conducting the analysis have been fulfilled and we can continue the analysis.

We subsequently run the IPMA by clicking on Calculate→Importance-Performance Map Analysis (IPMA) in the SmartPLS menu bar. Alternatively, you can left-click on the Calculate wheel symbol in the tool bar, and select the corresponding option in the combo box that opens. In the dialog box that opens (Figure 9), we need to specify the target construct and decide whether to include all the predecessor constructs of that target variable, or only those that have a direct relationship with it. We select USE as the target construct and choose the All Predecessors of the Selected Target Construct option. Most importantly, we need to specify each indicator's minimum and maximum value required for the rescaling of the data to a 0-100 scale. As shown in Figure 9, SmartPLS automatically reads these minimum and maximum values from the data. However, if the respondents have not made use of the full scale (e.g. the actual minimum value is 2 instead of 1), SmartPLS cannot correctly rescale the data. Consequently, the rescaled latent variable scores will not be between 0 and 100 but, for instance, between −5 and 95. In such a case, we need to manually insert the true minimum value of the scale (e.g. 1 instead of 2) by clicking on the corresponding cell in the Min column. Alternatively, we can simultaneously specify the minimum and maximum value of all the indicators. To do so, enter the corresponding values next to Min/Max at the bottom of the dialog box and click on Apply to All. In our example, all the respondents made use of the full range of the indicator scales as indicated in the Min and Max columns of the SmartPLS Data View (Figure 8). We therefore maintain the default settings and proceed by clicking on Start Calculation.

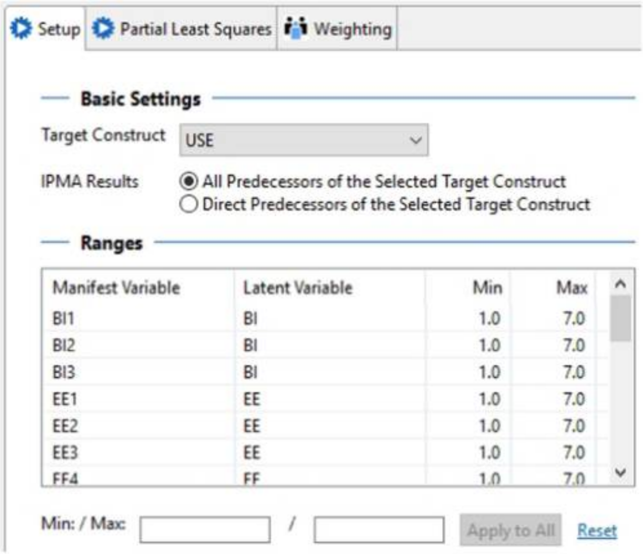



**Figure 9.**
SmartPLS IPMA dialog

SmartPLS now automatically computes the performance and importance values (Step 2 and 3) and creates the importance-performance map (Step 4). After completing the computations, SmartPLS opens the Results Report. Initially, it shows the results of the standardized path coefficients. Under Quality Criteria→Importance-Performance Map (USE) (Constructs), the report includes the importance-performance map as displayed in Figure 10. Under Final Results →Total Effects, SmartPLS displays the importance values in a matrix format. The graphical representation of the importance-performance uses the unstandardized total effects for the importance-dimension (x-axis), which you can access by clicking on the tabs Constructs, unstandardized and Indicators unstandardized. Under Final Results→Performance/Index, for the performance-dimension (y-axis), you can access the rescaled performance values of the latent and manifest variables (i.e. indicators) by means of the tabs LV Performances and MV Performances.

Not surprisingly, we find that the two direct predecessors, BI and FC, have a particularly high importance (Figure 10). Although performing at comparable levels, the FC construct has a considerably higher importance than the BI construct. Managerial actions should therefore prioritize improving the performance of the BI, which can be achieved by focusing on the predecessor construct of BI with the strongest impact on USE. As can be seen in Figure 10, EE has the strongest total effect on USE.

It is important to note that the graphical representation of IMPA results differs from the graphical PLS-SEM results illustration in SmartPLS. Instead of displaying the $R^2$ values of the endogenous latent variables in the PLS path model (Figure 6), the IPMA results show the performance values of each latent variable (Figure 11); instead of displaying the standardized outer loadings or weights (Figure 6), the IPMA results show the unstandardized and rescaled outer weights of the measurement models regardless if they are formative or reflective (Figure 11).

To gain more specific information on how to increase the performance of constructs, the following analyses focus on the indicator level (Step 5)[2].

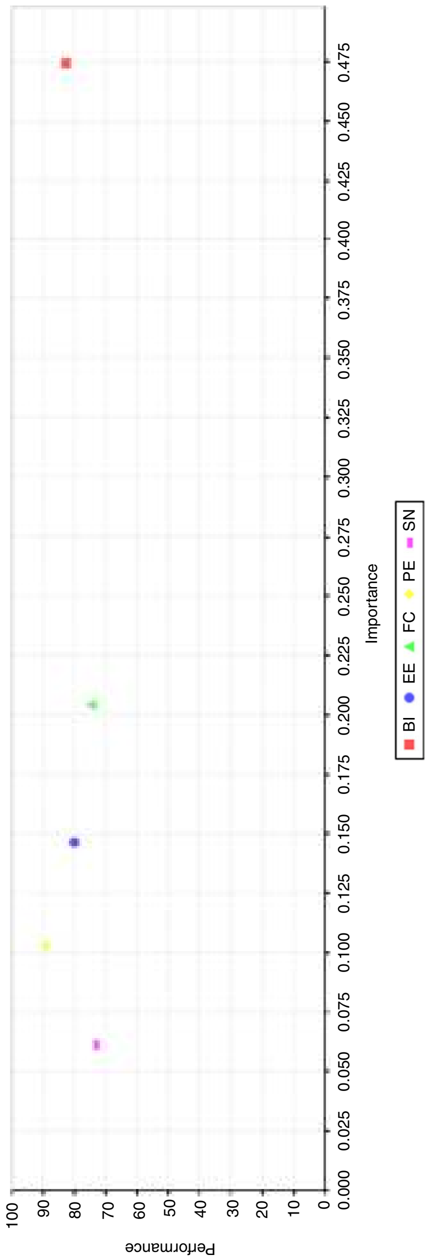



**Figure 10.**
Importance-performance map (construct level) of the target construct USE

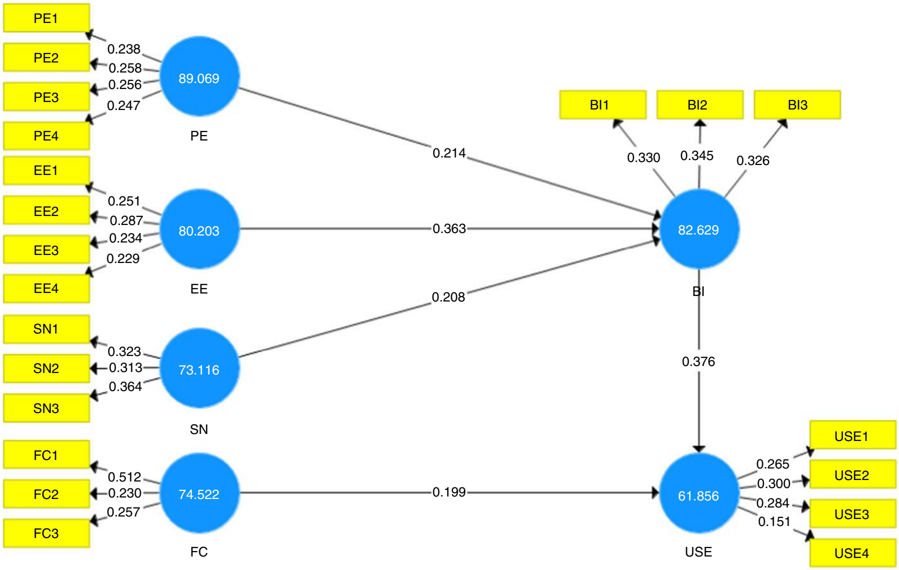



**Figure 11.**
PLS path model and IPMA results

In the results report, under Quality Criteria→Importance-Performance Map (USE) (Indicators), SmartPLS shows the indicators' importance-performance map as displayed in Figure 12. For example, we find that the indicator EE2 ("It is easy for me to become skillful using computers") has a relatively high importance when focusing on the construct EE, while offering some room for performance improvement. Hence, performance improvements could focus on offering high-quality computer trainings to provide users with the skills and knowledge they need. As a direct consequence, the performance of the construct EE increases, which entails an improvement of the construct BI and the target construct USE. Similarly, other indicators (e.g. FC1, "I have the resources and the knowledge and the ability to make use of the computer") may gain particular attention regarding improving the USE.

## Summary and conclusion

Review studies on the use of PLS-SEM (Hair *et al.*, 2012a, b; Ringle *et al.*, 2012; Sarstedt *et al.*, 2014) reveal that practically all researchers rely on standard PLS path model analysis, often ignoring more advances techniques, such as CTA-PLS (Gudergan *et al.*, 2008), FIMIX-PLS (Hahn *et al.*, 2002; Ringle *et al.*, 2010; Sarstedt *et al.*, 2011; Sarstedt and Ringle, 2010), PLS-POS (Becker *et al.*, 2015), moderator (Henseler and Chin, 2010; Henseler and Fassott, 2010), and multigroup analyses (Sarstedt *et al.*, 2011). The IPMA belongs to this suite of often neglected methods, but are particularly useful for generating additional findings and conclusions. By combining the analysis of the importance and performance dimensions, the IPMA allows for prioritizing constructs to improve a certain target construct. Expanding the analysis to the indicator level allows for identifying the most important areas of specific actions. These results are, for example, particularly important in studies researching the differing impacts that certain construct dimensions have on a phenomenon such as corporate reputation (e.g. Sarstedt *et al.*, 2013), or customer

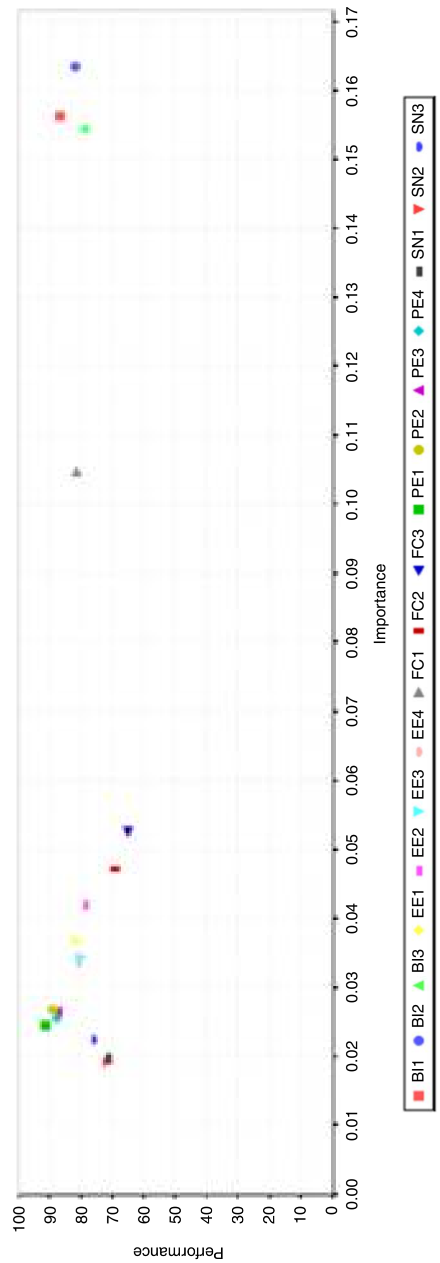



**Figure 12.**
Importance-performance map (indicator level) of the target construct USE

satisfaction (e.g. Ringle *et al.*, 2011). Another extension of the IPMA's use is in the context of a multigroup analysis. The IPMA allows for contrasting group results and for developing specific conclusions in respect of each group (Rigdon *et al.*, 2010, 2011; Schloderer *et al.*, 2014). However, researchers should refrain from using the IPMA if the analysis does not meet the requirements mentioned in Step 1 of the IPMA procedure (Figure 3) such as having only positive outer weights estimates in the measurement models.

As the IPMA assumes linear relationships, future research could focus on non-linear IPMA results (Anderson and Mittal, 2000; Eskildsen and Kristensen, 2006; Mittal *et al.*, 1998), making the analysis even more useful. For example, in the context of the Kano model, an IPMA could consider the differing role of delighters and basic needs (e.g. Kano *et al.*, 1984). If the performance of a delighter construct exceeds a certain threshold, further improvement of this construct's performance improves the target construct exponentially. Conversely, performance decreases in this construct generally have a lower effect on the target construct. The opposite holds for basic needs, where decreases in a corresponding construct's performance result in steep decreases in the target construct's performance. Exceeding the performance of basic needs above a certain threshold will, however, only marginally increase the target construct's performance. In this context, the penalty-reward contrast analysis of IPMA results (Matzler and Sauerwein, 2002; Matzler *et al.*, 2003) could be another promising avenue for future research. Given IPMA's capabilities and the additional benefit of potential extensions to non-linear effects, we expect that the much broader use of the method in future studies will extend the results presentations and allow more elaborate findings and conclusions.

## Notes

1. The original paper also considered a further model set-up with additional moderator variables (i.e. age, experience, gender, and voluntariness of use). However, in light of the problems that arise in the interpretation of total effects that include moderators, our analysis focuses on the first model in Al-Gahtani *et al.* (2007).
2. Note again that an IPMA on the indicator level is possible regardless of the predecessor constructs' measurement model specifications. However, an indicator-related analysis is particularly useful in formative measurement model settings.

## References

Al-Gahtani, S.S., Hubona, G.S. and Wang, J. (2007), "Information technology (IT) in Saudi Arabia: culture and the acceptance and use of IT", *Information & Management*, Vol. 44 No. 8, pp. 681-691.

Anderson, E.W. and Fornell, C.G. (2000), "Foundations of the American customer satisfaction index", *Total Quality Management*, Vol. 11 No. 7, pp. 869-882.

Anderson, E.W. and Mittal, V. (2000), "Strengthening the satisfaction-profit chain", *Journal of Service Research*, Vol. 3 No. 2, pp. 107-120.

Becker, J.-M., Ringle, C.M., Sarstedt, M. and Völckner, F. (2015), "How collinearity affects mixture regression results", *Marketing Letters*, Vol. 26 No. 4, pp. 643-659.

Bollen, K.A. and Bauldry, S. (2011), "Three Cs in measurement models: causal indicators, composite indicators, and covariates", *Psychological Methods*, Vol. 16 No. 3, pp. 265-284.

Bollen, K.A. and Diamantopoulos, A. (in press), "In defense of causal-formative indicators: a minority report", *Psychological Methods* (in press).

Chin, W.W. (1998), "The partial least squares approach to structural equation modeling", in Marcoulides, G.A. (Ed.), *Modern Methods for Business Research*, Erlbaum, Mahwah, NJ, pp. 295-358.

Chin, W.W. (2010), "How to write up and report PLS analyses", in Esposito Vinzi, V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series, Volume II)*, Springer, Heidelberg, Dordrecht, London and New York, NY, pp. 655-690.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical Models", *Management Science*, Vol. 35 No. 8, pp. 982-1003.

Dijkstra, T.K. and Henseler, J. (2015), "Consistent partial least squares path modeling", *MIS Quarterly*, Vol. 39 No. 2, pp. 297-316.

do Valle, P.O. and Assaker, G. (2015), "Using partial least squares structural equation modeling in tourism research: a review of past research and recommendations for future applications", *Journal of Travel Research* (in press).

Eskildsen, J.K. and Kristensen, K. (2006), "Enhancing importance-performance analysis", *International Journal of Productivity and Performance Management*, Vol. 55 No. 1, pp. 40-60.

Fornell, C.G., Johnson, M.D., Anderson, E.W., Cha, J. and Bryant, B.E. (1996), "The American customer satisfaction index: nature, purpose, and findings", *Journal of Marketing*, Vol. 60 No. 4, pp. 7-18.

Garson, G.D. (2014), *Partial Least Squares Regression and Structural Equation Models*, Statistical Associates, Asheboro, NC.

Grønholdt, L., Martensen, A., Jørgensen, S. and Jensen, M.J. (2015), "Customer experience management and business performance", *International Journal of Quality and Service Sciences*, Vol. 7 No. 1, pp. 90-106.

Gudergan, S.P., Ringle, C.M., Wende, S. and Will, A. (2008), "Confirmatory tetrad analysis in PLS path modeling", *Journal of Business Research*, Vol. 61 No. 12, pp. 1238-1249.

Hahn, C., Johnson, M.D., Herrmann, A. and Huber, F. (2002), "Capturing customer heterogeneity using a finite mixture PLS approach", *Schmalenbach Business Review*, Vol. 54 No. 3, pp. 243-269.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-151.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2013), "Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance", *Long Range Planning*, Vol. 46 Nos 1-2, pp. 1-12.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2010), *Multivariate Data Analysis*, Prentice Hall, Englewood Cliffs, NJ.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage, Thousand Oaks, CA.

Hair, J.F., Sarstedt, M., Pieper, T.M. and Ringle, C.M. (2012a), "The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications", *Long Range Planning*, Vol. 45 Nos 5-6, pp. 320-340.

Hair, J.F., Sarstedt, M., Ringle, C.M. and Mena, J.A. (2012b), "An assessment of the use of partial least squares structural equation modeling in marketing research", *Journal of the Academy of Marketing Science*, Vol. 40 No. 3, pp. 414-433.

Henseler, J. and Chin, W.W. (2010), "A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling", *Structural Equation Modeling*, Vol. 17 No. 1, pp. 82-109.

Henseler, J. and Fassott, G. (2010), "Testing moderating effects in PLS path models: an illustration of available procedures", in Esposito Vinzi, V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series, Volume II)*, Springer, Heidelberg, Dordrecht, London and New York, NY, pp. 713-735.

Henseler, J., Hubona, G.S. and Ray, P.A. (2016), "Using PLS path modeling in new technology research: updated guidelines", *Industrial Management & Data Systems*, Vol. 116 No. 1, pp. 1-16.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2012), "Using partial least squares path modeling in international advertising research: basic concepts and recent issues", in Okazaki, S. (Ed.), *Handbook of Research in International Advertising*, Edward Elgar Publishing, Cheltenham, pp. 252-276.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135.

Höck, C., Ringle, C.M. and Sarstedt, M. (2010), "Management of multi-purpose stadiums: importance and performance measurement of service interfaces", *International Journal of Services Technology and Management*, Vol. 14 Nos 2/3, pp. 188-207.

Kano, N., Seraku, N., Takahashi, F. and Tsuji, S.-i. (1984), "Attractive quality and must-be quality", *Journal of the Japanese Society for Quality Control*, Vol. 14 No. 2, pp. 147-156.

Kristensen, K., Martensen, A. and Grønholdt, L. (2000), "Customer satisfaction measurement at post denmark: results of application of the european customer satisfaction index methodology", *Total Quality Management*, Vol. 11 No. 7, pp. 1007-1015.

Lee, L., Petter, S., Fayard, D. and Robinson, S. (2011), "On the use of partial least squares path modeling in accounting research", *International Journal of Accounting Information Systems*, Vol. 12 No. 4, pp. 305-328.

Lohmöller, J.-B. (1989), *Latent Variable Path Modeling with Partial Least Squares*, Physica, Heidelberg.

Martensen, A. and Grønholdt, L. (2010), "Measuring and managing brand equity: a study with focus on product and service quality in banking", *International Journal of Quality and Service Sciences*, Vol. 2 No. 3, pp. 300-316.

Martensen, A., Dahlgaard, J.J., Park-Dahlgaard, S.M. and Grønholdt, L. (2007), "Measuring and diagnosing innovation excellence – simple contra advanced approaches: a Danish study", *Measuring Business Excellence*, Vol. 11 No. 4, pp. 51-65.

Martilla, J.A. and James, J.C. (1977), "Importance-performance analysis", *Journal of Marketing*, Vol. 41 No. 1, pp. 77-79.

Matzler, K. and Sauerwein, E. (2002), "The factor structure of customer satisfaction: an empirical test of the importance grid and the penalty-reward-contrast analysis", *International Journal of Service Industry Management*, Vol. 13 No. 4, pp. 314-332.

Matzler, K., Sauerwein, E. and Heischmidt, K.A. (2003), "Importance-performance analysis revisited: the role of the factor structure of customer satisfaction", *Service Industries Journal*, Vol. 23 No. 2, pp. 112-129.

Mittal, V., Ross, W.T. Jr and Baldasare, P.M. (1998), "The asymmetric impact of negative and positive attribute-level performance on overall satisfaction and repurchase intentions", *Journal of Marketing*, Vol. 62 No. 1, pp. 33-47.

Peng, D.X. and Lai, F. (2012), "Using partial least squares in operations management research: a practical guideline and summary of past research", *Journal of Operations Management*, Vol. 30 No. 6, pp. 467-480.

Richter, N.F., Sinkovics, R.R., Ringle, C.M. and Schlägel, C. (2015), "A critical look at the use of SEM in international business research", *International Marketing Review*, Vol. 33 No. 3, pp. 376-404.

Rigdon, E.E. (2012), "Rethinking partial least squares path modeling: in praise of simple methods", *Long Range Planning*, Vol. 45 Nos 5-6, pp. 341-358.

Rigdon, E.E. (2013), "Partial least squares path modeling", in Hancock, G.R. and Mueller, R.O. (Eds), *Structural Equation Modeling. A Second Course*, Information Age Publishing, Charlotte, NC, pp. 81-116.

Rigdon, E.E. (2014), "Rethinking partial least squares path modeling: breaking chains and forging ahead", *Long Range Planning*, Vol. 47 No. 3, pp. 161-167.

Rigdon, E.E., Ringle, C.M. and Sarstedt, M. (2010), "Structural modeling of heterogeneous data with partial least squares", *Review of Marketing Research*, Vol. 7, pp. 255-296.

Rigdon, E.E., Ringle, C.M., Sarstedt, M. and Gudergan, S.P. (2011), "Assessing heterogeneity in customer satisfaction studies: across industry similarities and within industry differences", *Advances in International Marketing*, Vol. 22, pp. 169-194.

Ringle, C.M., Sarstedt, M. and Mooi, E.A. (2010), "Response-based segmentation using finite mixture partial least squares: theoretical foundations and an application to American customer satisfaction index data", *Annals of Information Systems*, Vol. 8, pp. 19-49.

Ringle, C.M., Sarstedt, M. and Straub, D.W. (2012), "A critical look at the use of PLS-SEM in MIS quarterly", *MIS Quarterly*, Vol. 36 No. 1, pp. iii-xiv.

Ringle, C.M., Sarstedt, M. and Zimmermann, L. (2011), "Customer satisfaction with commercial airlines: the role of perceived safety and purpose of travel", *Journal of Marketing Theory and Practice*, Vol. 19 No. 4, pp. 459-472.

Ringle, C.M., Wende, S. and Becker, J.-M. (2015), "SmartPLS 3", SmartPLS GmbH, Bönningstedt.

Roldán, J.L. and Sánchez-Franco, M.J. (2012), "Variance-based structural equation modeling: guidelines for using partial least squares in information systems research", in Mora, M., Gelman, O., Steenkamp, A.L. and Raisinghani, M. (Eds), *Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems*, IGI Global, Hershey, PA, pp. 193-221.

Sarstedt, M. and Mooi, E.A. (2014), *A Concise Guide to Market Research: The Process, Data, and Methods Using IBM SPSS Statistics*, Springer, Berlin.

Sarstedt, M. and Ringle, C.M. (2010), "Treating unobserved heterogeneity in PLS path modelling: a comparison of FIMIX-PLS with different data analysis strategies", *Journal of Applied Statistics*, Vol. 37 No. 8, pp. 1299-1318.

Sarstedt, M., Hair, J.F., Ringle, C.M., Thiele, K.O. and Gudergan, S.P. (2016), "Estimation issues with PLS and CBSEM: where the bias lies!", *Journal of Business Research*, Vol. 69 No. 10, pp. 3998-4010.

Sarstedt, M., Henseler, J. and Ringle, C.M. (2011), "Multi-group analysis in partial least squares (PLS) path modeling: alternative methods and empirical results", *Advances in International Marketing*, Vol. 22, pp. 195-218.

Sarstedt, M., Wilczynski, P. and Melewar, T.C. (2013), "Measuring reputation in global markets – a comparison of reputation measures' convergent and criterion validities", *Journal of World Business*, Vol. 48 No. 3, pp. 329-339.

Sarstedt, M., Becker, J.-M., Ringle, C.M. and Schwaiger, M. (2011), "Uncovering and treating unobserved heterogeneity with FIMIX-PLS: which model selection criterion provides an appropriate number of segments?", *Schmalenbach Business Review*, Vol. 63 No. 1, pp. 34-62.

Sarstedt, M., Ringle, C.M., Smith, D., Reams, R. and Hair, J.F. (2014), "Partial least squares structural equation modeling (PLS-SEM): a useful tool for family business researchers", *Journal of Family Business Strategy*, Vol. 5 No. 1, pp. 105-115.

Schloderer, M.P., Sarstedt, M. and Ringle, C.M. (2014), "The relevance of reputation in the nonprofit sector: the moderating effect of socio-demographic characteristics", *International Journal of Nonprofit and Voluntary Sector Marketing*, Vol. 19 No. 2, pp. 110-126.

Slack, N. (1994), "The importance-performance matrix as a determinant of improvement priority", *International Journal of Operations and Production Management*, Vol. 44 No. 5, pp. 59-75.

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M. and Lauro, C. (2005), "PLS path modeling", *Computational Statistics & Data Analysis*, Vol. 48 No. 1, pp. 159-205.

Venkatesh, V. and Davis, F.D. (2000), "A theoretical extension of the technology acceptance model: four longitudinal field studies", *Management Science*, Vol. 46 No. 2, pp. 186-204.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.

Völckner, F., Sattler, H., Hennig-Thurau, T. and Ringle, C.M. (2010), "The role of parent brand quality for service brand extension success", *Journal of Service Research*, Vol. 13 No. 4, pp. 359-361.

Wold, H.O.A. (1982), "Soft Modeling: the basic design and some extensions", in Jöreskog, K.G. and Wold, H.O.A. (Eds), *Systems Under Indirect Observations: Part II*, North-Holland, Amsterdam, pp. 1-54.

## About the authors

Christian M. Ringle is a Chaired Professor of Management at the Hamburg University of Technology (TUHH) and Conjoint Professor at the Faculty of Business Law at the University of Newcastle. His widely published research addresses the management of organizations, strategic and human resource management, marketing, and quantitative methods for business and market research. He is the Cofounder of SmartPLS (www.smartpls.com), a statistical software tool with a graphical user interface for partial least squares structural equation modeling (PLS-SEM). He regularly teaches doctoral seminars on multivariate statistics, the PLS-SEM method, and the use of SmartPLS worldwide. Christian M. Ringle is the corresponding author and can be contacted at: ringle@tuhh.de

Marko Sarstedt is a Chaired Professor of Marketing at the Otto-von-Guericke-University Magdeburg and Conjoint Professor to the Faculty of Business and Law at the University of Newcastle. His main research is in the application and advancement of structural equation modeling methods to improve the understanding of consumer behavior and to improve marketing decision making. His research has been published in journals such as *Journal of Marketing Research*, *Journal of the Academy of Marketing Science*, *Organizational Research Methods*, *MIS Quarterly*, *International Journal of Research in Marketing* and *Long Range Planning*. He regularly teaches doctoral seminars on multivariate statistics, structural equation modeling, and measurement worldwide.

**This article has been cited by:**

1. HenselerJörg Jörg Henseler Department of Design, University of Twente, Enschede, The Netherlands NOVA Information Management School, Universidade Nova de Lisboa, Lisbon, Portugal . 2016. Guest editorial. *Industrial Management & Data Systems* **116**:9, 1842-1848. [Citation] [Full Text] [PDF]